ESSAYS IN MACROECONOMICS

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Essays in Macroeconomics

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Abstract

The dissertation studies the primary sources of business-cycle fluctuations and their interaction with uncertainty and financial frictions. In my work, I examine the degree to which changes in uncertainty and financial conditions can be independent drivers of economic fluctuations; I study the sources of boom-bust cycles and whether they are linked to credit market sentiments; and I ask how financial frictions affect economic fluctuations in terms of prices and quantities.

In “Financial and Uncertainty Shocks”, I separately identify financial and uncertainty shocks using a novel SVAR procedure and discusses their distinct monetary policy implications. The procedure relies on the qualitatively different responses of corporate cash holdings: after a financial shock, firms draw down their cash reserves as they lose access to external finance, while uncertainty shocks drive up cash holdings for precautionary reasons. Although both financial and uncertainty shocks are contractionary, my results show that the former are inflationary while the latter generate deflation. I rationalize this pattern in a New-Keynesian model: after a financial shock, firms increase prices to raise current liquidity; after an uncertainty

shock, firms cut prices in response to falling demand. These distinct channels have stark monetary policy implications: conditional on uncertainty shocks the divine coincidence applies, while in case of financial shocks the central bank can stabilize inflation only at the cost of more unstable output fluctuations.

In "What are the Sources of Boom-Bust Cycles?", joint with Vito Cormun, we provide a synthesis of two major views on economic fluctuations. One view maintains that expansions and recessions arise from the interchange of positive and negative persistent exogenous shocks to fundamentals. This is the conventional view that gave rise to the profusion of shocks used in modern dynamic stochastic general equilibrium models. In contrast, a second view, which we call the endogenous cycles view, holds that business cycle fluctuations are due to forces that are internal to the economy and that endogenously favor recurrent periods of boom followed by a bust. In this environment, cycles can occur after small perturbations of the long run equilibrium. We find empirical evidence pointing at the coexistence of both views. In particular, we find that the cyclical behaviour of economic aggregates is due in part to strong internal mechanisms that generate boom-bust phenomena in response to small changes in expectations, and in part to the interchange of positive and negative persistent fundamental shocks. Motivated by our findings, we build a theory that unifies the dominant paradigm with the endogenous cycles approach. Our theory suggests that recessions and expansions are intimately related phenomena, and that understanding the nature of an expansion, whether it is driven by fundamentals or by beliefs, is a first order issue for policy makers whose mandate is to limit the occurrance of inefficient economic fluctuations.

In “COVID-19 and Credit Constraints”, joint with Pierluigi Balduzzi, Emanuele Brancati, and Fabio Schiantarelli, we investigate the economic effects of the COVID-19 pandemic and the role played by credit constraints in the transmission mechanism, using a novel survey of expectations and plans of Italian firms, taken just before and after the outbreak. Most firms revise downward their expectations for sales, orders, employment, and investment, while prices are expected to increase at a faster rate, with geographical and sectoral heterogeneity in the size of the effects. Credit constraints amplify the effects on factor demand and sales of the COVID-19 generated shocks. Credit-constrained firms also expect to charge higher prices, relative to unconstrained firms. The search for and availability of liquidity is a key determinant of firms’ plans. Finally, both supply and demand shocks play a role in shaping firms’ expectations and plans, with supply shocks being slightly more important in the aggregate.

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Chapter 1

Financial and Uncertainty Shocks

1.1 Introduction

This paper shows how to separately identify two major sources of business-cycle fluctuations — financial shocks and uncertainty shocks — and what different monetary policy intervention they require. Although both financial and uncertainty shocks have contractionary effects on output, consumption, investment, and employment, my results reveal that financial shocks are associated with inflationary forces while uncertainty shocks trigger deflationary patterns. The monetary authority faces very different trade-offs: in case of uncertainty shocks, the divine coincidence applies; while, in case of financial shocks, the central bank can close the output gap only at the cost of more unstable inflation.

This paper provides three main contributions. First, I propose a novel structural VAR strategy that relies on the qualitatively different responses of corporate cash holdings to separately identify financial and uncertainty shocks on aggregate data. In support of the identifying assumption on corporate cash, I analyze a partial equilibrium model and provide a set of supportive evidence. Second, I identify the distinct empirical patterns associated with financial and uncertainty shocks on aggregate U.S. data. Empirical results reveal that, although both shocks have contractionary effects on key macroeconomic variables, financial shocks are associated with inflationary forces, while uncertainty shocks are related to deflationary patterns. Third, I integrate the partial equilibrium model presented above in a general equilibrium New Keynesian framework to rationalize the qualitatively different responses of inflation and conclude that the monetary authority deals with different challenges in face of the two shocks.

To support the identifying assumption that corporate cash displays a qualitatively different response to financial and uncertainty shocks, the first part of the paper analyzes a partial equilibrium model. In this infinite-horizon model, a continuum of firms maximize the expected present value of the dividend flow by choosing cash holdings after observing aggregate shocks but before observing the idiosyncratic productivity level. In the spirit of Riddick and Whited (2009), the model features financial frictions in the form of a dilution cost that firms have to pay if they have to issue negative dividends due to low idiosyncratic productivity. In case of a financial shock, captured by a current increase in the dilution cost of issuing negative dividends, firms prefer to draw down the stock of cash in order to avoid accessing external funds. In case of an uncertainty shock, captured by an increase in the variance of future technology shocks, firms prefer to invest current resources in the stock of cash for a precautionary motive. In other words, cash holdings can be seen as an insurance that firms implicitly purchase as a protection against the risk of future cash flow shortages. After a financial shock, the implicit cost of this insurance rises and firms opt to hold less of it; after an uncertainty shock, firms attribute more value to this insurance and opt to hold more of it.

The second part of the paper proposes a novel econometric strategy in a structural VAR context that uses the qualitatively different responses of corporate cash as an internal instrument to uniquely identify financial and uncertainty shocks without relying on any ordering assumption. The econometric procedure can be summarized in two steps. In the first step, the econometrician identifies financial and uncertainty shocks by maximizing two objective functions simultaneously. The objective function associated with the identification of financial shocks is increasing in the impact response of a proxy for financial conditions (i.e., the credit spread) and *decreasing* in the impact response of corporate cash. Importantly, the parameter δ governs the relative importance that this function gives to the response of financial conditions and of corporate cash holdings. At the same time, the objective function associated with the identification of uncertainty shocks is increasing in the impact response of a proxy for uncertainty (i.e., the expected volatility) and *increasing* in the impact response of corporate cash. Importantly, the *same* parameter δ governs the relative importance that this function gives to the response of measured uncertainty and of corporate cash holdings. In the second step, the econometrician selects δ^* such that the two types of shocks identified with the maximization problems described above are orthogonal to each other. Given δ^* — which I show exists and is unique under mild assumptions — financial and uncertainty shocks are uniquely identified. Thus, with this econometric procedure the econometrician can now rely on a point estimate rather than on a set of feasible solutions (as in the case of sign restrictions). In addition, this procedure does not rely on any ordering assumptions (as in the case of Cholesky identification) since neither type of shocks is identified before the other.

In the third part, I employ the econometric strategy presented above on aggregate U.S. data in order to quantify the effect of the two shocks on the real economy. The baseline specification is a ten-variable VAR with the excess bond premium (Gilchrist et al., 2017), measured macroeconomic uncertainty (Jurado et al., 2015), corporate cash holdings over total assets, GDP, consumption, investment, total hours, GDP deflator, the real stock of money (M2 over GDP deflator), and the federal funds rate. The impulse responses implied by my procedure show that financial and uncertainty shocks have contractionary effects on output, consumption, investment, and total hours. Meanwhile, financial shocks have a positive impact effect on GDP deflator, while uncertainty shocks have a negative and persistent effect on inflation. Finally, the federal funds rate displays a pronounced and persistent fall after an uncertainty shock and only a mild and marginally significant decrease after a financial shock.

Quantitatively, uncertainty shocks explain almost 20% of the variations in real GDP over a business-cycle frequency, while financial shocks explain about 40%. Although financial shocks appear to be a more important driver of business-cycle fluctuations, uncertainty shocks trigger a much larger effect on total hours: financial shocks explain roughly 20% of the forecast error variance of total hours, while uncertainty shocks explain almost 40%. In addition, financial shocks explain a large size of the forecast error variance of corporate cash and little of the one of GDP deflator over a business-cycle frequency. By contrast, uncertainty shocks explain less than a fifth in the case of corporate cash but more than 20% in the case of GDP deflator.

In the last part of the paper, I integrate the partial equilibrium model presented above in a New Keynesian framework with the aim to: (i) confirm that the economic intuition on cash is robust to general equilibrium forces, (ii) rationalize the differential empirical response of inflation to financial and uncertainty shocks, and (iii) derive monetary policy implications. The model is a standard New Keynesian model (see Gilchrist et al., 2017) augmented with good-specific habits, costly external finance, and a market for cash and liquid assets. In line with Ravn et al. (2006), the household good-specific demand depends also on an external habit stock determined by previous levels of the good-specific consumption. Firms can influence the future value of the good-specific habit stock, which operates as a customer base, by changing prices. Moreover, following the partial equilibrium model described above, all external finance takes the form of equity and financial frictions are featured by a dilution cost that firms have to pay when issuing negative dividends. Finally, the model features a market for cash and liquid assets where households receive utility from holding cash, while firms hold cash as a device to have more financial flexibility.

The general equilibrium forces magnify the qualitatively different effects that financial and uncertainty shocks have on corporate cash holdings. In case of financial shocks, the stochastic discount factor decreases because households expect the effects of the contraction to die out in the near future; viceversa, in case of uncertainty shocks, the same variable increases because households expect larger consumption variance in the future. As a result, after a financial shock, households are more impatient and push firms to cut corporate cash holdings in order to distribute more dividends today. Conversely, after an uncertainty shock, households are more patient and, due to a precautionary motive, put pressure on firms to increase current savings in order to receive more dividends in future. Moreover, if we consider the effect of inflation, it turns out that inflationary (deflationary) forces create an incentive to draw down (build up) the stock of cash because, for a given nominal interest rate, the benefit of holding cash and liquid assets decreases (increases). Thus, as long as the model is consistent with the empirical results of inflationary financial shocks and deflationary uncertainty shocks, inflation is also pushing corporate cash holdings in the expected direction.

Regarding the effect of financial and uncertainty shocks on inflation, the different response works through the good-specific habit — that results in a customer base — and the costly external finance. Specifically, the existence of a customer base with low demand elasticity gives firms the incentive to raise prices when they need to generate internal sources of finance. As a result, the response of inflation depends on two forces that move prices in two different directions. First, the need to generate internal sources of finance that is associated with inflationary forces and, second, the overall fall in demand that, in line with textbook demand shocks, is related to deflationary patterns. In the case of a financial shock, firms increase prices because they want to generate additional internal resources in order to avoid the costlier external finance. Conversely, after an uncertainty shock, the need to generate current internal finance is not largely affected, while the fall in the overall demand (for a precautionary motive) encourages firms to cut prices. Using a large set of reasonable calibrations, simulations robustly confirm this intuition.

I conclude by studying the monetary policy implications of my model for financial and uncertainty shocks. Conditional to the latter, the positive comovement between output and inflation suggests that the divine coincidence is in place and the monetary authority can simultaneously close the output gap and the inflation gap. Conversely, the negative comovement between output and inflation after a financial shock suggests that the central bank has to deal with a non-trivial trade-off between the output gap and the inflation gap. I formally analyze this intuition by running a counter-factual policy experiment where the monetary authority pays more attention to the output gap relative to the inflation gap. In the case of uncertainty shocks, the further attempt to stabilize the output gap implies an even further stabilization of the inflation gap; while, in the case of financial shocks, the monetary authority stabilizes the output gap only at the cost of higher inflation.

Related literature. This paper contributes to different strands of the literature. The econometric procedure presented here relates to other papers proposing the use of internal instruments to identify structural shocks in a VAR context.[1] First, this paper is related to Faust (1998) and Uhlig (2005) that introduce the penalty function

[1] See Stock and Watson (2018) on a comparison and discussion between external and internal instruments on structural VARs.

approach. I contribute to this literature by proposing an econometric strategy that uses a specific type of penalty function to disentangle two shocks that have a qualitatively different effect on a observable variable. In addition, this project is also related to a series of papers that introduce and develop sign-restriction set identification procedures such as Faust (1998); Canova and De Nicoló (2002); Peersman (2005); Uhlig (2005); Fry and Pagan (2011); and Rubio-Ramírez et al. (2010). I contribute to this literature by providing a methodology that uses qualitative assumptions to provide a unique solution to the structural VAR system without relying on any ordering assumptions.

Regarding the empirical identification of either financial or uncertainty shocks or both, this project relates to those papers, such as Bloom (2009), Basu and Bundick (2017), and Leduc and Liu (2016), that use a recursive ordering to identify the effects of uncertainty shocks on real variables. I contribute to this literature by providing empirical evidence that does not rely on recursive ordering assumptions. Moreover, this project is also related to Jurado et al. (2015) who also use the Cholesky identification but provide a more refined proxy for economic uncertainty. I contribute to this paper by disentangling from their proxy the part explained by financial shocks. Moreover, this project is related to Berger et al. (2017), who identify uncertainty shocks as second-moment news shocks on realized volatility and find that uncertainty shocks have negligible effects on real variables. I contribute to this paper by providing an alternative method, which does not rely on any zero impact restrictions, to identify uncertainty shocks. Finally, this project is also related to Ludvigson et al. (2020) who use a novel identification strategy based on a set of assumptions on the features of the estimated shock series to identify financial uncertainty shocks together with economic uncertainty shocks. They find that financial uncertainty shocks have large and adverse effects on the economy while adverse economic uncertainty shocks have positive and significant effects on the same variables. I differ in terms of the objective since my aim is to identify financial shocks, which can possibly include second moment financial shocks (see Section 1.4.2), from macroeconomic uncertainty shocks. In addition, I use a different econometric strategy which relies on a single identifying assumption and provides a unique solution.[2]

Moreover, I am also related to those papers that show the empirical effect of financial shocks on the economy. First, Gilchrist and Zakrajšek (2012) provide two novel variables, the GZ credit spread and the excess bond premium, to proxy for time-varying financial conditions. They show that those variables have a large predictive power on real variables and explain a large portion of economic activity. I contribute to this paper by disentangling from the innovations in the excess bond premium the part explained by uncertainty shocks.[3] Moreover, Gilchrist et al. (2017) use firm-level data to show that credit-constrained firms increased prices during the Financial Crisis to boost their internal sources of finance, while their unconstrained counterparts cut prices.[4] Although my analysis uses aggregated data

[2] See also Carriero et al. (2018), Angelini et al. (2019), Caggiano et al. (2020), and Colombo and Paccagnini (2020a) for other econometric strategies and evidence regarding the economic effects of financial uncertainty shocks and/or macroeconomic uncertainty shocks. See also Cascaldi-Garcia et al. (2020) for a survey.

[3] Related to Gilchrist and Zakrajšek (2012), see also Gambetti and Musso (2017) and Colombo and Paccagnini (2020b) for other empirical evidence on the effects of financial shocks.

[4] See also Asplund et al. (2005), de Almeida (2015), Kimura (2013), Lundin et al. (2009), and Montero and Urtasun (2014) for additional evidence supporting this mechanism. Kim (2020), instead,

and controls for the presence of uncertainty shocks, I obtain analogous inflationary patterns in response to financial shocks.[5] Moreover, this project is closely related to the empirical contribution by Furlanetto et al. (2019) who identify different types of financial shocks in the same VAR system. In the second part of the paper, they also disentangle credit shocks from uncertainty shocks and find that the latter ones have negligible effects on real variables. My empirical evidence differs from this last exercise for two main reasons. First, my focus is specifically on economic uncertainty shocks while their estimated uncertainty shocks are mostly associated with financial uncertainty because they use the VIX as a proxy for uncertainty.[6] Second, my exercise aims to show the qualitative difference between financial and uncertainty shocks, while their focus is on their quantitative importance. A closely related paper that also inspired my analysis is Caldara et al. (2016). They show lower and upper bounds of the effects of financial and uncertainty shocks using the penalty function approach together with ordering assumptions. They find that both shocks explain a sizable fraction of output over a business-cycle frequency. My project contributes to this paper in two ways. First, my identification strategy provides point estimates within their bounds to specifically quantify the respective effects of the two shocks on real variables. In addition, I empirically find qualitatively different effects of

provides evidence that firms facing an adverse financial shock reduce prices in the short run to liquidate inventories and generate cash flow, followed by a price increase in the medium run.

[5] See Abbate et al. (2016) for an analogous empirical result on U.S. aggregate data using a structural VAR with sign restrictions.

[6] The VIX, as shown by Ludvigson et al. (2020) and as argued at the end of Section 1.4.2 later on, is much more related to first- and second-moment financial shocks rather than to economic uncertainty shocks.

financial and uncertainty shocks on inflation and derive the associated monetary policy implications.

Finally, the model presented in this project is related to those theoretical contributions that analyze the effects of either financial shocks or uncertainty shocks or both. Regarding the effects of financial shocks the model presented here shares many elements with the one by Gilchrist et al. (2017) that also rationalizes the inflationary patterns associated with financial shocks. I contribute to their model by adding a market for cash and liquid assets and by showing that, together with corporate cash holdings, inflation also displays qualitatively different patterns in response to financial and uncertainty shocks.[7] Regarding the theoretical effects of uncertainty shocks, this project is related to the early contribution of Bloom (2009) that proposes a model with capital partial irreversibilities to rationalize the large drop in investment after an uncertainty shock. Moreover, the model presented here is also related to Leduc and Liu (2016) and Basu and Bundick (2017) who show that in New Keynesian general equilibrium models uncertainty shocks have the same flavor as demand shocks and generate business-cycle comovements among hours, consumption and investment.[8] I contribute to this literature by providing an analysis of the deflationary effects of uncertainty shocks together with the inflationary effects of financial shocks, and by deriving associated monetary policy implications.

[7] On models that analyze the effects of financial shocks see Jermann and Quadrini (2012) for an early contribution. Moreover, see also Bacchetta et al. (2019) for a model in which corporate liquidity can be used to distinguish between credit shocks and liquidity shocks. Among other contributions, see also Christiano et al. (2010) and Khan and Thomas (2013).

[8] For theoretical models that analyze the effects of different types of uncertainty shocks see also Justiniano and Primiceri (2008), Fernández-Villaverde et al. (2011), Christiano et al. (2014), Fernández-Villaverde et al. (2015), and Bloom et al. (2018). See Fernández-Villaverde and Guerrón-Quintana (forthcoming) for a survey.

Regarding theoretical contributions with both financial and uncertainty shocks, the model presented in this project is closely related to Gilchrist et al. (2014) and Alfaro et al. (2018). Both models feature financial frictions and partial irreversibilities of capital together with financial and uncertainty shocks. I contribute to this literature emphasizing the qualitative different effect of the two shocks.

1.2 Identifying assumption on corporate cash holdings

This section argues that financial and uncertainty shocks have a qualitatively different impact effect on aggregate corporate cash holdings. Intuitively, corporate cash is expected to fall after a financial shock since firms use those reserves as a substitute for the costly external finance, while the stock of corporate cash is expected to rise after an uncertainty shock for a precautionary motive. Section 1.2.1 formalizes this argument with a partial equilibrium model, while Section 1.2.2 shows some reduced-form suggestive evidence that confirms the empirical relevance of my identifying assumption.

1.2.1 Firm model

Firms are indexed by i and seek to maximize the expected present value of a the following dividend flow,

$$\mathbb{E}_t \left[\sum_{s=0}^{\infty} \beta^s d_{i,t+s} \right]$$

where $\beta \in (0, 1)$ represents the deterministic discount factor and $d_{i,t}$ represents the dividend flow defined by the flow-of-funds constraint

$$d_{i,t} = a_{i,t} A_t + R^x x^f_{i,t-1} + g(x^f_{i,t-1}) - x^f_{i,t} + \varphi_t \min\{0, d_{i,t}\}.$$

Variable $a_{i,t}$ is the realized level of idiosyncratic productivity which is i.i.d. across firms and over time, and has cumulative distribution function $F(\cdot)$; and A_t is the realized level of aggregate productivity which is i.i.d. over time. Variable $x^f_{i,t}$ represents end-of-period corporate cash holdings, $R^x < 1/\beta$ is the interest paid on cash saved in the previous period, and $g(\cdot)$ is a positive, increasing, and concave function which captures the benefit of the financial flexibility given by the availability of cash holdings.[9] Moreover, all external finance takes the form of equity and φ_t is a dilution cost which implies that when firms issue negative dividends $d_{i,t} < 0$, the actual flow from the issuance is reduced by $\varphi_t d_{i,t}$. As argued by Riddick and Whited (2009), this simplification allows to emphasize the interaction between technology, financial frictions, and cash holdings.[10]

Firm i chooses optimal cash $x_{i,t}$ after observing productivity A_t and the aggregate shocks, but before knowing the realized idiosyncratic productivity $a_{i,t}$. Following Kiley and Sim (2014) and Gilchrist et al. (2017), this timing assumption implies that firms are identical ex ante and the subscript i can be suppressed. There are

[9] As discussed in the survey by Strebulaev and Whited (2012), corporate cash holdings provide financial flexibility for near-term obligations such as payment of salaries and wages, taxes, bills for goods and services rendered by suppliers, rent, utilities, and debt services.

[10] The simplest formulation of this type of financial frictions comes from Gomes (2001). See also Bolton et al. (2011) for a model with analogous financial frictions and corporate cash in continuous time. In addition, see the survey by Strebulaev and Whited (2012) Sections 3.2 and 3.3 for a detailed description.

two possible aggregate shocks: financial shocks ε_t^F which affect the dilution cost φ_t (Gilchrist et al., 2017) such that $\varphi_t = \varphi_{ss} + \varepsilon_t^F$; and uncertainty shocks ε_t^U which affect the variance σ_t^A of future aggregate technology A_{t+1} (Leduc and Liu, 2016) such that $\sigma_t^A = \sigma_{ss}^A + \varepsilon_t^U$. For simplicity I assume that there is no persistence in the exogenous processes for σ_t^A and φ_t.

The first order condition for corporate cash $x_{i,t}^f$, after invoking symmetry across i, implies

$$1 = E_t\left\{\beta\frac{\xi_{t+1}}{\xi_t}\left[R^x + g'\left(x_t^f\right)\right]\right\} \tag{1.1}$$

where $\xi_t = 1 + \varphi_t/(1-\varphi_t) \times F(\bar{a}_t)$ is the multiplier of the flow-of-funds constraint and $R_t^x + g'(x_t^f)$ is the future marginal benefit of holding cash. In addition, $\bar{a}_t = 1/A_t \times \left[x_t^f - x_{t-1}^f - g(x_{t-1}^f)\right]$ is the threshold for idiosyncratic productivity such that $d_t = 0$ and $F(\bar{a}_t)$ is the probability of issuing negative dividends.

Proposition 1 provides the main motivation for my empirical approach to separately identify financial and uncertainty shocks on aggregate data.

Proposition 1 *Financial shocks decrease corporate cash x_t^f, while uncertainty shocks increase corporate cash x_t^f.*

Proof. The right-hand side of Equation 1.1 is monotonically decreasing in a financial shock ε_t^F. The right-hand side of Equation 1.1 is monotonically increasing in an uncertainty shock ε_t^U. The latter statement is true because $1/A_{t+1}$ is a convex function and, due to the Jensen's inequality, the expectation of a convex function increases after a mean-preserving spread. Since the right-hand side of Equation 1.1

is monotonically decreasing in end-of-period cash holdings x_t^f , it must be the case that in order to satisfy the equality of Equation 1.1, x_t^f decreases after a financial shock ε_t^F and increases after an uncertainty shock ε_t^U. ■

The intuition of Proposition 1 comes directly from the first order condition for corporate cash (Equation 1.1). Note that the multiplier ξ_t disciplines the current need of internal resources and, the larger its value, the greater the incentive to generate current internal liquidity. In case of financial shocks, ξ_t rises because of the higher cost of external finance and firms prefer to draw down the stock of cash in order to avoid or limit accessing external funds. In case of uncertainty shocks, the expected value of ξ_{t+1} rises because of the additional risk of a future cash flow shortfall (due to the mean-preserving spread in future aggregate technology), and firms prefer to invest current resources in end-of-period cash holdings for a precautionary motive. In other words, cash holdings x_t^f can be interpreted as an insurance that firms implicitly purchase *today* as a protection against the risk of cash flow shortages *tomorrow*. After a financial shock, the implicit cost of this insurance rises and firms opt to hold less of it; after an uncertainty shock, firms attribute more value to this insurance and opt to hold more of it.

1.2.2 Supportive Evidence

The objective of this section is to show some supportive evidence to confirm the empirical relevance of the identifying assumption on corporate cash.

Table 1.1 shows the correlations among aggregate corporate cash, a proxy for financial conditions, and a proxy for uncertainty across different data treatments.

Following Bacchetta et al. (2019), corporate cash holdings (x_t^f) is defined as the sum of private foreign deposits, checkable deposits and currency, total time and saving deposits, and money market mutual fund shares over total assets for the non-financial corporate sector. As a proxy for financial conditions, I decide to use the excess bond premium (f_t) by Gilchrist and Zakrajšek (2012) because is an aggregate measure of credit spread that controls for the expected default risk of the borrowers. Among all available proxies of uncertainty, I prefer to use the macroeconomic uncertainty (u_t) by Jurado et al. (2015) for two reasons. First, it is estimated with a stochastic volatility model which provides series orthogonal to current economic innovations. This characteristic is particularly useful to make sure that my analysis is not confounding the effect of other first-moment shocks. Second, since my identifying assumption builds on a theoretical prediction, this variable is particularly convenient because it refers to a type of uncertainty shocks on which there is large consensus on how should be featured in a model.[11]

The first column displays the correlation of the excess bond premium f_t with macroeconomic uncertainty u_t. Across different data treatments, the correlation remain positive, large, and highly significant. This result is not surprising as it represents the econometric challenge of separately identifying financial and uncertainty shocks. As the exogenous processes for financial and uncertainty shocks cannot be observed, the econometrician needs to rely on the endogenous counterparts – f_t and u_t, respectively – which display an analogous contemporaneous response in

[11] I will consider different types of uncertainty – using an a-theoretical approach – on Section 1.4.2.

Table 1.1: Correlation of corporate cash with key endogenous variables

	corr(f_t,u_t)	corr(f_t,x_t^f)	corr(u_t,x_t^f)
1. Series, no trend	0.66773*** (3.7333e-19)	-0.11982 (0.16157)	0.22208*** (0.0088478)
2. Residuals, no trend	0.52594*** (4.1193e-11)	-0.12205 (0.15538)	0.4378*** (8.8008e-08)
3. Series, quadratic trend	0.70225*** (8.2501e-22)	-0.18503** (0.029806)	0.10557 (0.21785)
4. Residuals, quadratic trend	0.51463*** (1.2491e-10)	-0.14637* (0.087883)	0.42118*** (2.9749e-07)
5. Series, BP filter	0.70172*** (9.1098e-22)	-0.37708*** (5.1445e-06)	0.082759 (0.33454)
6. Residuals, BP filter	0.58332*** (7.4378e-14)	-0.25699*** (0.0024334)	0.14891** (0.08244)
7. Series, HP filter	0.73708*** (6.6106e-25)	-0.26109*** (0.0019811)	0.086978 (0.3104)
8. Residuals, HP filter	0.49685*** (6.6044e-10)	-0.16101* (0.060162)	0.42697*** (1.9602e-07)

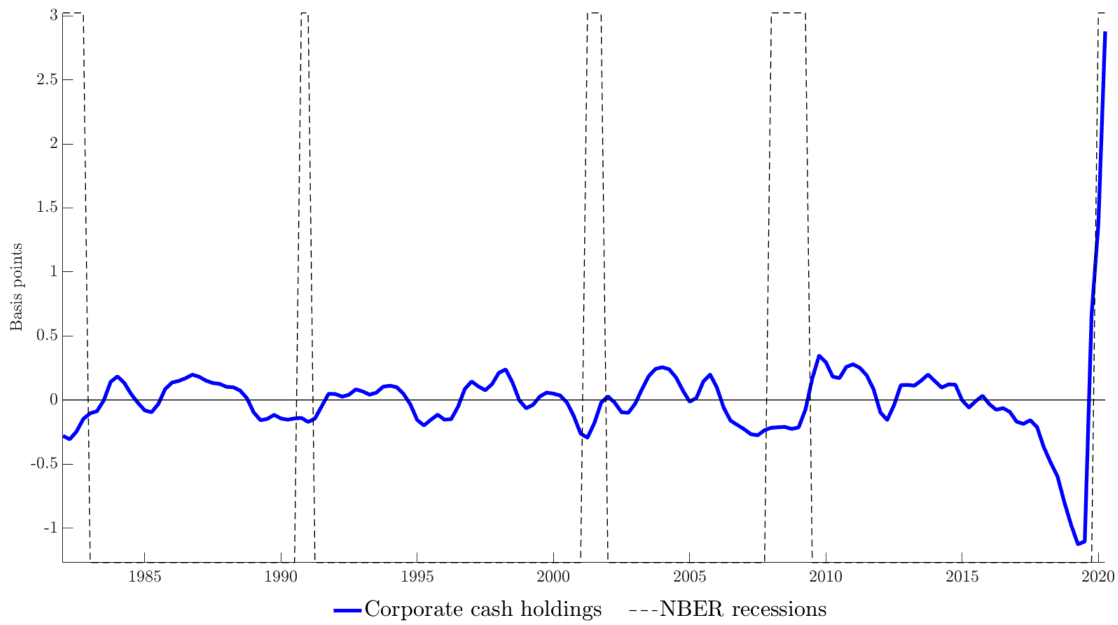
Notes. f_t is the excess bond premium by Gilchrist and Zakrajsek (2012), u_t is macroeconomic uncertainty by Jurado et al. (2015), and x_t^f is corporate cash holdings over total assets of from the Flow of Funds. Residuals are from a three variables VAR(1) with f_t, u_t, and x_t. P-values in parenthesis and *** p<0.01, ** p<0.05, * p<0.1.

face of the two shocks. This implies that, without any further assumption, it is not possible to separately identify financial shocks and uncertainty shocks.

The second and third columns display the correlations of the corporate cash x_t^f respectively with the excess bond premium f_t and the macroeconomic uncertainty u_t across different data treatments. The key result of this table is that although f_t and u_t are highly positively correlated with each other, corporate cash x_t^f captures a source of the heterogeneous variation between the two variables as it is correlated with opposite signs to f_t and u_t. In particular, as predicted by the model presented in Section 1.2.1, changes in the excess bond premium f_t are always negatively correlated with variations in corporate cash x_t^f, and, in most of the cases, this correlation is significant. At the same time, consistent with the model, changes in macroeconomic uncertainty u_t are always positively correlated with variations in corporate cash x_t^f, and, in most of the cases, this correlation is significant.

Figure 1.1 shows the aggregate corporate cash with the aim of building a narrative on the behavior of this variable during the latest recessions. First, if we focus on the 2001 Recession we observe a pronounced fall of corporate cash. This result is in line with the theoretical prediction presented above because this recession is associated with a huge financial market disruption and should be intimately related to the present of adverse financial shocks. In addition, focusing on the recent Covid-19 Recession, we observe a huge increase in the share of cash held by the non-financial corporate sector. Also in this case, the empirical pattern supports the identifying assumption because during the crisis there has be a spike in the uncertainty without a proportional financial market disruption thanks to the prompt interventions of

Figure 1.1: Aggregate corporate cash holdings and NBER recessions



Notes. Corporate cash is defined as corporate cash over total assets of non-financial corporate firms from the Flow of Funds. Variable is de-trended with the HP filter.

the Federal Reserve. Thus, the Covid-19 Recession is related to adverse uncertainty shocks without a large financial market disruption, which implies that firms are actually using their external finance to build a larger stock of cash as a buffer against the uncertain evolution of the crisis. Finally, focusing on the Great Recession, we do not observe a clear pattern for the behavior of corporate cash since it is quite stable during the onset of the crisis with a moderate spike during the final part. As I will describe later on, this result will be fully consistent with the empirical results because during the Great Recession, the US economy experiences the peculiar case where adverse financial and uncertainty shocks are simultaneously hitting the economy.

1.3 Econometric strategy

After motivating the identifying assumption, this section presents the econometric strategy and discuss its performance on simulated data from the model in Section 2.3.

1.3.1 Procedure

Consider a dynamic system $Y_t = [\ f_t,\ u_t,\ x_t^f,\ \ldots\ ]$ where f_t is a proxy for financial conditions such as the credit spread; u_t is a proxy for economic uncertainty such as the expected forecast error variance on macroeconomic variables; and x_t^f is corporate cash holdings. Other variables can be embedded in the system without affecting the econometric procedure. The reduced form VAR is,

$$Y_t = B(L)Y_{t-1} + i_t \tag{1.2}$$

where $i_t i_t' = \Sigma$ is the variance-covariance matrix of the reduced-form innovations $i_t = [\ i_t^f,\ i_t^u,\ i_t^x,\ \cdots\ ]$. The objective is to identify the structural shocks of interest (financial shocks ε_t^F and uncertainty shocks ε_t^U) from the reduced-form innovations i_t with the structural impact matrix A^*, such that $A^*\varepsilon_t = i_t$, $\varepsilon_t\varepsilon_t' = I$ and $\varepsilon_t = [\ \varepsilon_t^F,\ \varepsilon_t^U,\ \cdots\ ]$.

Assume that econometricians have the following three pieces of information:

1. Adverse financial shocks ε_t^F has a positive impact effect on variable f_t, and a negative impact effect on the corporate cash x_t^f.

2. Adverse uncertainty shocks ε_t^U has a positive impact effect on variable u_t and x_t^f.

3. Other shocks have a negligible impact effect on f_t and u_t.

The first two assumptions are justified by the theoretical model and reduced-form evidence presented in Section 1.2. The last assumption, instead, is justified by the empirical observation that the residuals of the excess bond premium by Gilchrist and Zakrajšek (2012) and of the macroeconomic uncertainty by Jurado et al. (2015) are orthogonal to a large series of structural shocks previously identified by the literature. With this last empirical observation, financial shocks ε_t^F and uncertainty shocks ε_t^U can be directly identified without controlling for any other structural shocks in the economy. In addition, in Section 1.4.2 I show that the estimated shock series are orthogonal to other structural shocks previously identified by the literature implying that any ex ante control would be unnecessary. As a result, other shocks affecting the economy can be treated as residuals which can have a contemporaneous effect only on cash. Notice that although is reasonable to assume that an uncertainty shock has a positive impact effect on f_t and a financial shock has a positive effect on u_t, I do not need to explicitly make this assumption but I will leave the two responses unconstrained.

With these elements in hand, I am ready to define the econometric procedure.

Definition 1 *Decompose $A^* = CD^*$ where C is the Cholesky decomposition of Σ and $D^* = [\ d_1^*,\ d_2^*,\ \cdots\ ]$ is an orthogonal matrix where:*

1. *Column vector d_1^* is the solution of the following problem,*

$$d_1^* = argmax_{d_1}\{(1-\delta^*)e_1Cd_1 - \delta^* e_3 Cd_1 \quad \textit{subject to} \quad d_1^{'}d_1 = 1\}; \tag{1.3}$$

2. *Column vector d_2^* is the solution of the following problem,*

$$d_2^* = argmax_{d_2}\{(1-\delta^*)e_2Cd_2 + \delta^* e_3 Cd_2 \quad \textit{subject to} \quad d_2^{'}d_2 = 1\}; \tag{1.4}$$

3. *$\delta^* \in (0,1)$ is such that $d_1^{*'}d_2^* = 0$.*

Notice that e_i is a raw vector with one in the i-th position and zeros elsewhere; Cd_1 and Cd_2 represent the impact of a one percent financial shock ε_t^F and a one percent uncertainty shock ε_t^U, respectively; and δ^* is a scalar that takes a real value strictly between zero and one.

Intuitively, in Problem 1.3, the impact effect of a financial shock is identified by maximizing a function that is increasing in the impact response of financial conditions f_t (e_1Cd_1) and *decreasing* in the impact response of cash x_t^f (e_3Cd_1); where the parameter δ^* governs the relative importance that this function gives to the two impact responses. Similarly, in Problem 1.4, the impact effect of an uncertainty shock is identified by maximizing a function that is increasing in the impact response of measured uncertainty u_t (e_2Cd_2) and *increasing* in the impact response of cash x_t^f (e_3Cd_2); where the *same* parameter δ^* governs the relative importance that this function gives to the two impact responses. In addition, note that the two conditions above are subject to the normalization $d_i^{'}d_i = 1$ since both column vectors are part of the orthogonal matrix D^*. Thus, for a given δ^*, Condition 1.3 imposes that ε_t^F must have a positive impact effect on f_t and a negative impact effect on x_t^f. Alternatively, for a given δ^*, the second item imposes that ε_t^U must have a positive effect on its endogenous counterpart u_t and on corporate cash x_t^f. Condition 3 selects a δ^* such that the two vectors d_1^* and d_2^* are orthogonal to each other as they are part of the orthogonal matrix D^*.

Together with Definition 1, I can now state the main technical result of the econometric strategy. Its formal proof is in Appendix A.2.

Proposition 2 *If corr*$(i_t^f, i_t^u) > 0$, *solution* δ^*, d_1^*, *and* d_2^* *exists.*

The proof can be explained intuitively. Consider Problems 1.3 and 1.4 as a function of a value of δ^* – say δ – that does not necessarily satisfy Condition 3. When δ is equal to zero then $d_1^*(\delta = 0)$ and $d_2^*(\delta = 0)$ maximize the impact effect on f_t and u_t, respectively. In other words, $d_1^*(\delta = 0)$ and $d_2^*(\delta = 0)$ solve a Cholesky identification problem where f_t and u_t are placed on top, respectively. Since $corr(i_t^f, i_t^u) > 0$, then $d_1^*(\delta = 0)'d_2^*(\delta = 0) > 0$. Alternatively, when δ is equal to one, then $d_1^*(\delta = 1)$ and $d_2^*(\delta = 1)$ maximize the impact effect on $-x_t^f$ and x_t^f, respectively. In other words, $d_1^*(\delta = 1)$ and $d_2^*(\delta = 1)$ solve a Cholesky identification problem where $-x_t^f$ and x_t^f are placed on top, respectively. This implies, by construction, that $d_1^*(\delta = 1)'d_2^*(\delta = 1) = -1$. Invoking the continuity of solutions $d_1^*(\delta)$ and $d_2^*(\delta)$ in function of δ, it follows that also $d_1^*(\delta)'d_2^*(\delta)$ is a continuous function of δ. As a result, it must be the case that, moving from $\delta = 0$ to $\delta = 1$, function $d_1^*(\delta)'d_2^*(\delta)$

crosses the zero line at least once confirming that δ^* such that $d_1^*(\delta^*)'d_2^*(\delta^*) = 0$ does exist.

Proving uniqueness is more challenging. In Appendix A.3 I show that under the assumption that financial conditions f_t and measure uncertainty u_t are perfectly correlated then a solution always exists and is unique. In addition, both on actual data and simulated data I have never met a single case where two δ^* exist in the same system.

Finally, in order to test the reliability of the econometric procedure, I simulate data from the model described in Section 2.3 and use this econometric strategy to identify financial and uncertainty shocks only using variables of which empirical counterpart can be observed in the data. Using small samples generated by a realistic calibrated version of the model, it appears that the procedure is able to recover more than 96% of the two unobservable shocks on average. Moreover, using the same simulated data I test the effectiveness of my econometric strategy against sign restrictions. Estimated responses point out that my econometric strategy outperforms sign restrictions to recover the model-implied impulse responses. See Appendices A.4 and A.5 for details and results.

1.3.2 Comparison with other methodologies

Since Sims (1980) the Cholesky identification has been used to identify a plethora of shocks in the literature. For example, Christiano et al. (2005) estimate monetary policy shocks as innovations to the federal funds rate which do not have a contemporaneous effect on macroeconomic variables but they have an impact effect on fast-moving variables such as the growth rate of money. Although appealing for its simplicity, no plausible recursive assumptions can be used when aiming to identify financial and uncertainty shocks. As already argued by Caldara et al. (2016), this is the case because both proxies for financial conditions and uncertainty are fast-moving variables and simultaneously respond to financial and uncertainty shocks.

A similar problem appears with the penalty function approach (Faust, 1998; Uhlig, 2005). For example Caldara et al. (2016) identify financial and uncertainty shocks maximizing a penalty function with measured uncertainty and credit spreads. Although more general than a Cholesky identification, their identification scheme still needs an ordering assumption. As a result, Caldara et al. (2016) provides upper and lower bounds of the quantitative effects of financial and uncertainty shocks conditionally on the ordering assumption.

Moreover, my identification strategy is conceptually close to sign restrictions (Faust, 1998; Canova and De Nicoló, 2002; Peersman, 2005; Uhlig, 2005; Rubio-Ramírez et al., 2010; Fry and Pagan, 2011). Although sign restrictions on the same impact responses provide useful insights of the effects of financial and uncertainty shocks, my identification strategy is more convenient mainly for two reasons. First, this novel approach identifies financial shocks (uncertainty shocks) as the ones that maximize the response of financial conditions (measured uncertainty) conditional on controlling for uncertainty shocks (financial shocks). In other words, this procedure emphasizes the idea that the two shocks should have the maximum effect on their endogenous counterpart using corporate cash as a control to avoid any confounding effect. This feature is particularly appealing because the econometrician does not have to take a stand on the degree of endogeneity of the variables she is using. For example, if the endogenous proxies for financial conditions and macroeconomic uncertainty were fully exogenous, this strategy would be able to perfectly recover the two shocks by automatically imposing δ equal to zero. Second, this procedure does not impose any sign restrictions on the responses, but it imposes that the response of corporate cash after a financial shock should be relatively lower than the response of corporate cash after an uncertainty shock. Specifically, with this strategy the econometrician can identify the two shocks even if the response of corporate cash would be negative in face of the two shocks but relatively more negative in case of financial shocks. This feature allows for an additional degree of flexibility which makes the identifying assumption less restrictive. Besides, I also compare the effectiveness of my identification strategy to recover the actual impulse responses with the effectiveness of sign restrictions using simulated data from the model presented in Section 2.3. As hinted above, results suggest that – at least in this case – my identification strategy outperforms sign restrictions to recover the true responses implied by the model. See Appendix A.5 for details and results.

In addition, following Stock et al. (2012), a potential avenue to identify financial and uncertainty shocks is by using external instruments. As discussed by Stock and Watson (2018), with a valid instrument in hand, it is possible to obtain a consistent analysis of the shock of interest. However, as emphasized by Stock et al. (2012) and Caldara et al. (2016), finding an instrument correlated only with financial or uncertainty shocks is not an easy task and no valid candidates have been proposed so far.[12]

Finally, Ludvigson et al. (2020) propose a strategy, known as “shock-based restrictions", that imposes quantitative and qualitative restrictions directly on the series of the estimated shocks rather than on the impulse response functions. This procedure can be an alternative tool to disentangle financial shocks and uncertainty shocks given the specific assumptions on the sign and timing of the shocks. In addition, Caggiano et al. (2020) use a similar approach where they impose (among other conditions) that around specific dates financial shocks (uncertainty shocks) explain the most of their endogenous counterpart. Although both approaches can be suitable and can be seen as complements to my procedure, the main benefit of my strategy is of being free from a set of narrative-based restrictions.

1.4 Financial and uncertainty shocks on U.S. aggregate data

In this section, I simultaneously identify financial and uncertainty shocks on U.S. aggregate data using the identifying assumption on aggregate cash holdings presented in Section 1.2 together with the econometric strategy presented in Section 1.3.

[12] Note that Forni et al. (2017), using the intuition that news on future outcomes have both first and second moment effects, use the square of identified news shocks as a proxy for uncertainty shocks in a VARX context. Their measure for uncertainty shocks can be interpreted as an instrument (or a proxy) which is possibly uncorrelated with financial shocks. In addition, Piffer and Podstawski (2018) identify uncertainty shocks using as an instrument the variations of gold around specific dates.

1.4.1 Baseline specification and main results

In the baseline specification I estimate a reduced-form VAR with (i) credit spread as the level of the excess bond premium (EBP) by Gilchrist and Zakrajšek (2012); (ii) measured uncertainty as macroeconomic uncertainty at a three-month horizon by Jurado et al. (2015); (iii) corporate cash holdings as the level of corporate cash over total assets from the Flow of Funds; (iv) the log-transformation of real GDP; (v) the log-transformation of real consumption defined as consumption of non-durables plus consumption of services; (vi) the log-transformation of real investment defined as consumption of durables plus domestic investment; (vii) the log-transformation of total hours as hours of all persons in the non-farm business sector; (viii) the log-transformation of the GDP deflator; (ix) the log-transformation of the stock of money M2 over the GDP deflator; and (x) the shadow federal funds rate (FFR) by Wu and Xia (2016). In order to focus on the post-Volcker era, data range from the first quarter of 1982 to the second quarter of 2019 and, following the Bayesian Information Criterion (BIC), reduced-form innovations are obtained controlling for one lag of all the variables in the system.[13]

[13] The excess bond premium by Gilchrist and Zakrajšek (2012) is a measure of credit spread after controlling for firm-level characteristics. With this procedure they aim to provide a proxy for financial conditions orthogonal to economic fundamentals. In addition, Jurado et al. (2015) define macroeconomic uncertainty as the expected forecast error variance of more than 100 economic variables. To estimate these expected forecast error variances they use a stochastic volatility model which provides series orthogonal to current economic fundamentals. With these series they then build an index for uncertainty at different horizons. Finally, following Bacchetta et al. (2019), corporate cash holdings is defined as the sum of the level of: (i) private foreign deposits, (ii) checkable deposits and currency, (iii) total time and saving deposits and (iv) money market mutual fund shares. These variables refer to the nonfinancial corporate business sector. See Appendix B.9 for more details on data sources.

Figure 1.2a shows responses to a one percent financial shock. First, both the excess bond premium and the macroeconomic uncertainty display a positive and significant impact response. Following the identification assumption, corporate cash falls on impact and, in about two years, returns to its steady state value. Output, consumption, investment, and hours fall in the short run returning to their steady state values in two-three years. In line with the evidence and model by Gilchrist et al. (2017), the GDP deflator significantly jumps suggesting that financial shocks are associated with inflationary forces. Finally, in line with the response of prices, financial shocks trigger only a mild decrease in the federal fund rate that falls for only a few quarters after one year and half.

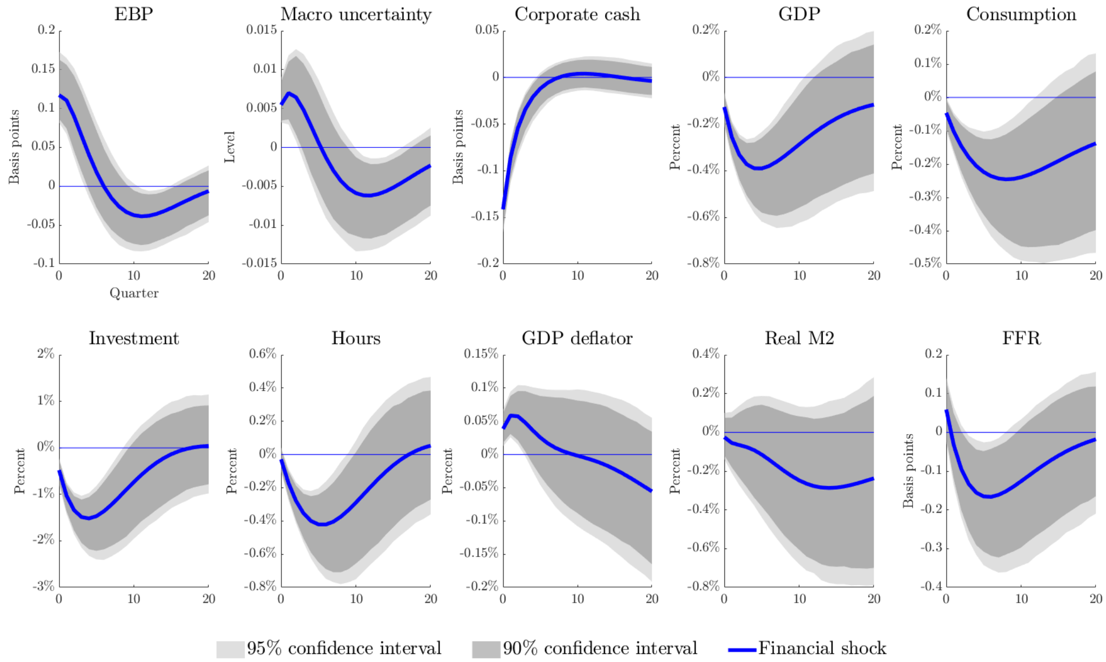
Figure 1.2b shows impulse responses to a one percent uncertainty shock. Also in this case, both the excess bond premium and measured macroeconomic uncertainty display a positive and significant impact response to an uncertainty shock, confirming the simultaneous response of those two variables to financial and uncertainty shocks. Corporate cash responds significantly on impact and displays a delayed build-up response which lasts almost five years. Analogously to financial shocks, uncertainty shocks trigger a contraction in output, consumption, investment, and hours; in case of output, consumption, and investment the effect lasts for about three years and a half, while in the case of total hours, the effect remains significant for almost five years. In addition, uncertainty shocks are robustly associated with deflationary forces – as shown by the fall in the GDP deflator – together with an increase in the real stock of money and a pronounced response of the monetary authority. The deflationary effect of uncertainty shocks is in line with the empirical evidence and theoretical arguments of Leduc and Liu (2016) and Basu and Bundick (2017).

Importantly, the different response of nominal variables provides important insights on the nature of business cycle fluctuations. First, the fact that those two identified shocks display an ex post different effect on other variables confirms my hypothesis that, besides the labeling of financial and uncertainty shocks, there are two distinct structural forces associated with the simultaneous innovations in measured uncertainty and credit spreads. Second, this different response of inflation suggests that disentangling financial and uncertainty shocks may have important monetary policy implications. In Section 2.3 I will rationalize the different response of prices to the two shocks and discuss potential trade-offs faced by the monetary authority.

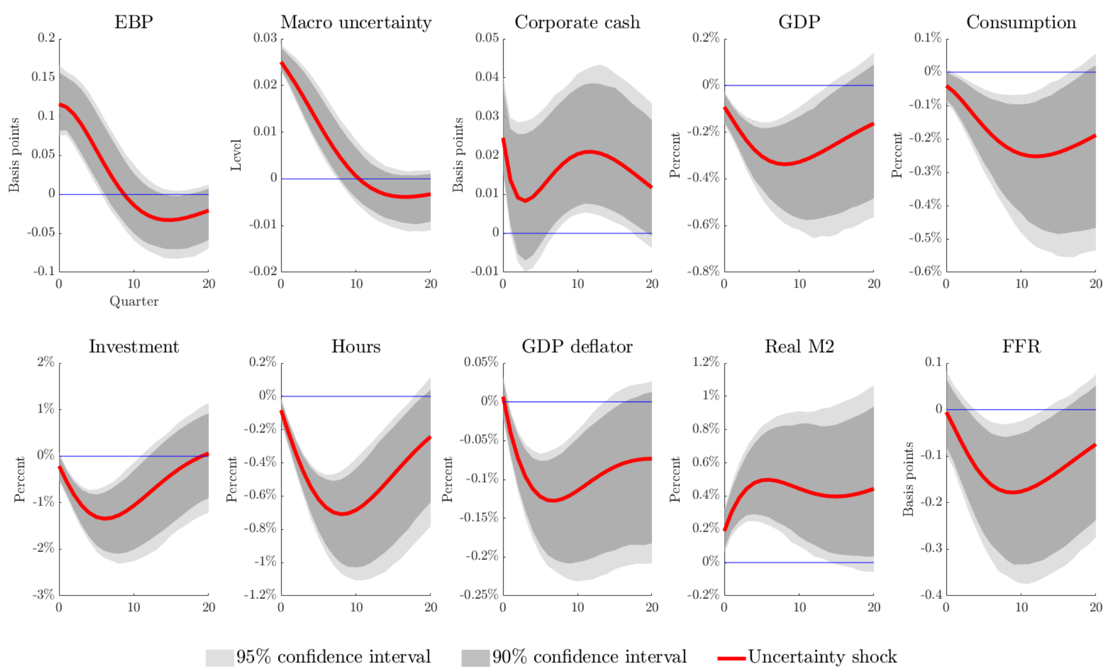
Figure 1.3 shows the forecast error variance of the endogenous variables in the system explained by financial shocks (blue solid lines) and uncertainty shocks (red solid lines). Financial shocks trigger about 25% of the unexpected fluctuations in the excess bond premium over business-cycle frequencies, and explain little of macroeconomic uncertainty. In line with the argument of the financial flexibility (see Strebulaev and Whited, 2012), corporate cash holdings seem to be mostly affected by financial shocks (about 90%) in the short run, and this effect slowly dies out over time. Financial shocks explain about 40% of real GDP over the six-quarter horizon and roughly 20%, 40%, and 20% of consumption, investment, and total hours over the same period. Finally, these shocks explain little of the GDP deflator, the real stock of money, and the shadow federal funds rate rate. In contrast, un-

Figure 1.2: Estimated impulse responses on U.S. aggregate data

(a) Financial shocks



(b) Uncertainty shocks

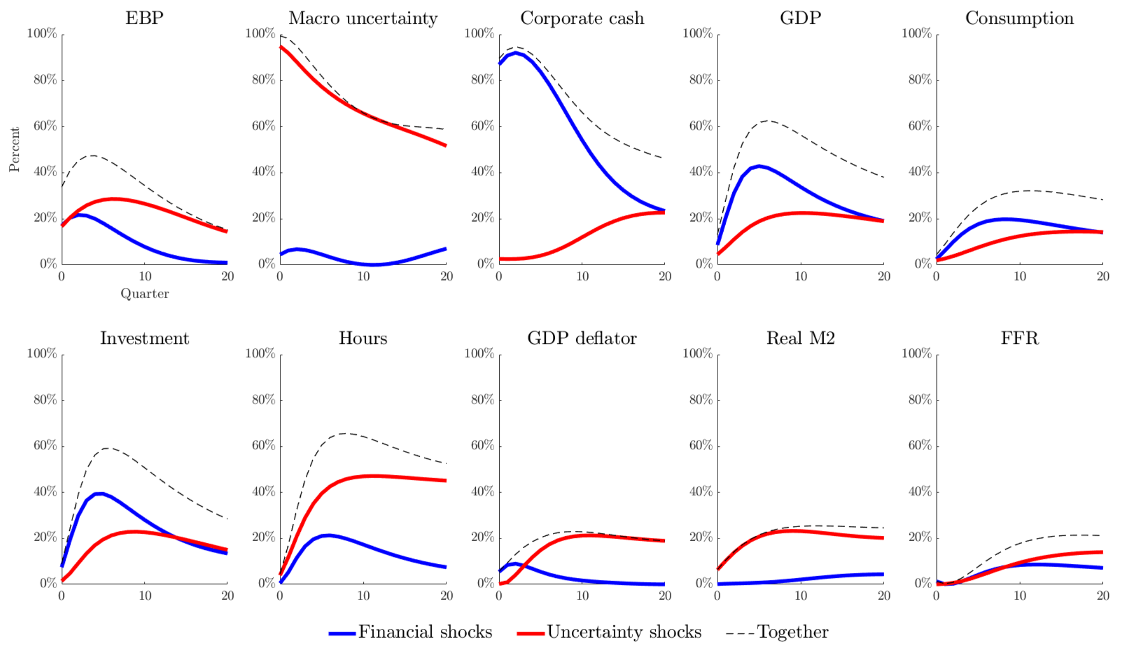


Notes. Data range: 1982:q2-2019:q2. VAR has one lag (BIC). Confidence intervals are obtained using standard Bayesian techniques (Sims and Zha, 1999). See Appendix B.9 for variable descriptions.

certainty shocks (red solid lines) trigger about 20% of the unexpected fluctuations in the excess bond premium over short-run horizons, and this effect dies out in the medium run. Macro uncertainty seems to be mostly affected by uncertainty shocks on impact (about 90%) even if this large effect dies out over time. In the short run uncertainty shocks do not have a remarkable quantitative effect on corporate cash, but this effect builds up over time reaching up to 20% in the five-year horizon. In addition, those shocks explain almost 20% of real GDP between the first and fourth year and roughly 15% of consumption and investment over the medium run. Interestingly, uncertainty shocks have a large quantitative effect (more than 40%) on total hours at business cycle frequencies. Finally, these shocks explain more than 20% of the GDP deflator and the real stock of money over business-cycle frequency, and about 15% of the shadow rate over a five-year horizon.

In summary, this analysis suggests three main conclusions. First, both shocks have sizable contractionary effects on macroeconomic variables and, although financial shocks seem to be a stronger driver of business cycle fluctuations, uncertainty shocks trigger a much larger effect on total hours. Second, prices (together with the real stock of money) display qualitatively different responses to financial and uncertainty shocks making the case relevant for monetary policy implications. Third, macroeconomic uncertainty measured by Jurado et al. (2015) seems to be more exogenous than the excess bond premium by Gilchrist and Zakrajšek (2012) as shown by the forecast error variance decomposition.

Figure 1.3: Estimated forecast error variance on U.S. aggregate data



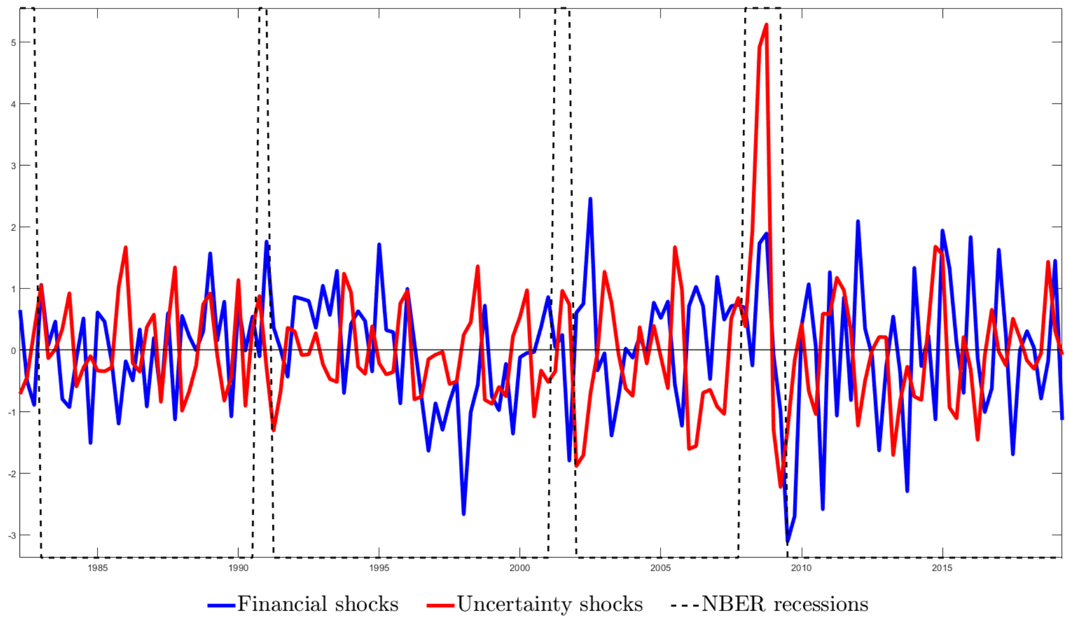
Notes. Forecast error variance estimated from baseline estimation. See Appendix B.9 for variable descriptions.

1.4.2 Shocks series, robustness, and financial uncertainty shocks

This section has three main objectives: (i) it shows the estimated shocks series to discuss their respective roles played during major U.S. economic contractions; (ii) it presents evidence that the two identified shocks are exogenous to a set of structural shocks previously identified by the literature; (iii) it provides a set of extensions to the baseline specification useful to inform on the robustness of the results and on the role played by financial uncertainty shocks in the U.S. economy.

Figure 1.4 shows the estimated shocks series on US aggregate data. There are two relevant adverse financial shocks in 1994 and 2003 as showed by the blue solid line. In addition, there are two large expansionary financial shocks before the early 2000s recession which are possibly associated with the formation of the dot-

Figure 1.4: Financial and uncertainty shocks series



com bubble. Interestingly, in 1998 the level of inflation was slightly below the 2% confirming that a non-inflationary financial expansion was playing a relevant role during that period. Finally, at the end of 2009 and 2010, there are two large contractionary financial shocks associated with the credit crunch of the Financial Crisis. On the other hand, uncertainty shocks (red solid line) do not display remarkable peaks over time except for two huge spikes during the Financial Crisis. Thus, in line with Stock et al. (2012), both financial and uncertainty shocks played an important role during the Financial Crisis, and my estimation suggests that financial shocks and uncertainty shocks contributed to 45% and 55% of the contraction in output experienced during the Great Recession, respectively.

Table 1.2 displays the correlation between financial and uncertainty shocks identified from the baseline specification presented in Section 1.4.1 with other structural shocks. The main takeaway is that no correlations are significant at a 10% level.

Table 1.2: Correlation with other structural shocks

	Financial shocks	Uncertainty shocks	Original source
Military News	-0.075 (0.384)	-0.107 (0.220)	Ramey (2016)
Expected Tax	-0.081 (0.438)	0.034 (0.741)	Leeper et al. (2013)
Monetary Policy	0.162 (0.106)	0.001 (0.993)	Romer and Romer (1989)
Technology Surprise	-0.113 (0.195)	0.012 (0.891)	Basu et al. (2006)

Notes. All the shocks, with the exception of technology surprises, are available on Valerie Ramey's website. Technology surprises are estimated as residuals from an AR(1) process using utilization-adjusted total factor productivity (Basu et al., 2006) available on the San Francisco Fed website. P-values in parenthesis and *, **, *** indicate statistical significance at the 10%, 5%, and 1%, respectively.

Nevertheless, monetary policy shocks (Romer and Romer, 1989) are correlated with financial shocks at the very border of the 10% significance level. To make sure that monetary policy shocks are not playing any role in the identification of financial shocks, as a robustness check I re-estimated the VAR system with those shocks ordered first. All the results presented so far are robust to this additional control (see Table 1.3) confirming that any ex ante control would be unnecessarily and confirms the empirical fact, discussed in Section 1.3, that innovations in the excess bond premium by Gilchrist and Zakrajšek (2012) and innovations in measured uncertainty by Jurado et al. (2015) are orthogonal to other structural forces previously identified.

In Table 1.3 I show the correlation between the shocks identified from the baseline specification with financial and uncertainty shocks identified from a set of robustness checks and extensions. Baseline results appear to be quite robust to a series of perturbations. Specification (1) allows the number of lags to vary accordingly to the Hannan-Quinn information criterion.[14] Specifications (3) and (4) estimate three-dimensional and seven-dimensional VARs, respectively. Specification (4), (5), (6), and (7) use different proxies for financial conditions. Specifications (8), (9), (10), (11) and (12) use different proxies for measured uncertainty. Moreover, Specification (13) uses an alternative definition of cash holdings, Specification (14) uses variables per capita, Specification (15) starts in the first quarter of 1990, and Specification (16) controls for monetary policy shocks. Finally, Specification (17) models the stance of the monetary policy using the shadow federal funds rate by Wu and Xia (2016). See notes in Table 1.3 for additional details.

In most cases there is little to learn except the fact that results are not particularly affected by the perturbations listed above. Nevertheless, it is important to highlight results in Specification (7) and Specification (12). Following Bloom (2009), Specification (12) uses the VIX as a proxy for macroeconomic uncertainty. In this case, uncertainty shocks remain correlated with their baseline counterpart only at 38% while financial shocks barely change. Even if not shown, those estimated uncertainty shocks trigger no significant effects on real variables and, consequently, do not explain any of the variations in output, consumption, investment and hours. On the other hand, in Specification (7) I use the VIX as a proxy for financial conditions instead of the credit spread. In this case, both estimated shocks remain highly correlated with their baseline counterpart. In particular, in the case of financial shocks the correlation with its baseline counterpart is 84%.

[14] I exclude the Akaike Informartion Criterion (AIC) since it requires 8 lags: definitely to large for the number of observations and the number of endogenous variables.

Table 1.3: Correlation with robustness checks and extensions

Specification	Robustness	Financial Shocks	Uncertainty Shocks
(1)	HQ: 2 lags	0.88	0.82
(2)	Dimension: 3 variables	0.91	0.91
(3)	Dimension: 7 variables	0.98	0.98
(4)	Credit spread: GZ	0.97	0.99
(5)	Credit spread: BAA10Y	0.93	0.98
(6)	Credit spread: FU3	0.81	0.95
(7)	Credit spread: VIX	0.84	0.95
(8)	Uncertainty: MU1	1	0.99
(9)	Uncertainty: MU12	0.99	0.96
(10)	Uncertainty: RU3	1	0.84
(11)	Uncertainty: FU3	0.95	0.53
(12)	Uncertainty: VIX	0.86	0.38
(13)	Cash: plus Treasury	0.83	0.97
(14)	Per Capita	1	1
(15)	Start: 1990Q1	0.92	0.97
(16)	MP shocks control	0.98	1
(17)	FFR: shadow rate	0.99	1

Notes. Specifications (1) uses two lags to estimate reduced-form innovations following the HQ criterion. Specification (2) is a three-dimensional system with measured uncertainty, excess bond premium and corporate cash. Specification (3) is a seven-dimensional system with all the variables of the baseline except the GDP deflator, Real M2, and FFR. Specification (4), (5), (6), and (7) use the GZ spread (Gilchrist and Zakrajšek, 2012), the Moody's Baa spread at 10 years, financial uncertainty at three months (Jurado et al., 2015), and the VIX as a proxy for financial conditions, respectively. Specifications (8), (9), (10), (11) and (12) use one-month macroeconomic uncertainty (Jurado et al., 2015), 12-months macroeconomic uncertainty (Jurado et al., 2015), three-month real uncertainty (Jurado et al., 2015), three-month financial uncertainty (Jurado et al., 2015), and the VIX as a proxy for measured uncertainty, respectively. Specification (13) adds to the definition of corporate cash holdings also the level of treasury securities for the nonfinancial corporate sector. Specification (14) uses the log of GDP, consumption, investment and hours per capita. Specification (15) starts in the first quarter of 1990. Specification (16) controls for monetary policy shocks. Specification (17) models the stance of monetary policy with the shadow federal funds rate (Wu and Xia, 2016).

This result suggests two conclusions. First, the VIX is not a proper substitute for measured macroeconomic uncertainty because its innovations (see also Ludvigson et al., 2020) are mostly related to uncertainty concerning financial conditions. Second, the VIX is a legitimate substitute for the credit spread because also second moment financial shocks have a negative effect on corporate cash holdings. As a result financial shocks as estimated by my identification strategy are general financial shocks which capture a mix between first and second moment shocks which directly arise from the financial sector. This conclusion is also supported by Specifications (6) and (11) where I use financial uncertainty by Ludvigson et al. (2020) as a proxy for financial conditions and economic uncertainty, respectively. Financial uncertainty works much better as a proxy for financial conditions — financial shocks are correlated up to 81% — rather than as a proxy for economic uncertainty — uncertainty shocks are correlated only at 53%.

This result can be rationalized with a risk-averse financial intermediary that, observing a larger level of financial uncertainty, decreases the supply of loans and increases the cost of borrowing. Although the model presented in Section 2.3 is way too simple to capture this idea, micro-founding financial frictions with the presence of a risk-averse financial intermediary can rationalize the fact that financial shocks and financial uncertainty shocks affect the economy through an analogous mechanism. Thus, according to those empirical results, financial shocks can be interpreted as a general object that embodies a family of first- and second-moment shocks that specifically arise within the financial market. Although possibly interesting, the objective of disentangling financial first-moment shocks from financial second-moment shocks is beyond the aim of this project.

1.5 Theory

In this section I integrate the partial equilibrium model presented in Section 1.2.1 in a general equilibrium framework with nominal frictions (Rotemberg, 1982) and households with good-specific habits (Ravn et al., 2006; Gilchrist et al., 2017). The model presented in this section has three main objectives: (i) confirming that the economic intuition presented in Section 1.2.1 is robust to controlling for general equilibrium forces; (ii) rationalizing the different empirical response of inflation to financial and uncertainty shocks shown in Section 1.4; and (iii) deriving monetary policy implications.

1.5.1 Model description

The economy is populated by (i) a continuum of utility-maximizing households that choose the habit-adjusted consumption bundle q_t, leisure $1 - n_t$, cash holdings (and/or liquid assets) X_t^h, and risk-free bonds B_t^h; (ii) a continuum of value-maximizing firms $i \in [0, 1]$ that make pricing and production decisions in order to maximize the present discount value of dividends; (iii) and a monetary authority that sets the nominal risk-free rate R_t and affects the nominal stock of cash in the economy $\bar{X}_t$.

Households

The model contains a continuum of identical households that consumes a variety of consumption goods indexed by $i \in [0, 1]$. The preferences of households are defined over a habit-adjusted consumption bundle q_t, leisure $1-n_t$, and beginning-of-period real cash holdings $x_{t-1}^h = X_{t-1}^h / P_{t-1}$ as follows

$$\mathbb{E}_t \sum_{s=0}^{\infty} \beta^s \left[\frac{(q_{t+s})^{1-\gamma_q}}{1-\gamma_q} + \chi_n \log(1 - n_{t+s}) + \chi_x \log(x_{t-1}^h) \right]; \quad 0 < \beta < 1.$$

where X_{t-1}^h is the nominal stock of cash hold at the beginning of the period and P_t is the aggregate price index. Following Gilchrist et al. (2017), the habit consumption aggregator is defined as

$$q_t \equiv \left[\int_0^1 \left(\frac{c_{i,t}}{s_{i,t-1}^{\theta}} \right)^{1-\frac{1}{\eta}} di \right]^{\frac{1}{1-\frac{1}{\eta}}}; \quad \theta < 0 \quad \text{and} \quad \eta > 0$$

where $c_{i,t}$ denotes the amount of a good of variety i consumed by the representative household at time t and $s_{i,t}$ is the external habit stock associated with good i. The law of motion of external habit is $s_{i,t} = \rho_s s_{i,t-1} + (1-\rho)c_{i,t}$ with $0 < \rho < 1$. Parameters θ and η govern the intensity of the good-specific habit and the elasticity of substitution across differentiated goods, respectively. The cost-minimization problem solved by the household gives rise to a good-specific demand (see Appendix A.7.1 for derivations) which is going to be relevant in the firms' maximization problem presented in the following section.

In addition, the household maximizes present value of utility subject to the following budget constraint

$$\tilde{p}_t q_t + \frac{B_t}{P_t} + \frac{X_t^h}{P_t} = w_t n_t + R_{t-1}\frac{B_{t-1}}{P_t} + R_{t-1}^x \frac{X_{t-1}^h}{P_t} + \tau_t.$$

Note that the budget constraint is expressed in real terms since $\tilde{p}_t q_t$ is the cost of the consumption bundle over the aggregate price index P_t. In addition, $w_t = W_t/P_t$ is the real wage, R_{t-1} is the nominal interest rate, set by the monetary authority, on previous period risk-free bonds B_{t-1}, R_{t-1}^x is the nominal interest rate on previous period cash and liquid assets X_{t-1}^h, and τ_t represents a series of real transfers that in every period the central authority and the firms make to the households. Optimality conditions, formally derived in Appendix A.7.2, give rise to the inter-temporal Euler equation for risk-free bonds, the labor supply, and the demand of real cash and liquid assets x_t^h. The two former optimality conditions are standard, while the latter takes the following form,

$$x_t^h = \beta \chi_x \frac{R_t}{R_t - R_t^x} \lambda_t^{-1}.$$

Intuitively, the demand for cash is increasing in χ_x and R_t^x which represent the taste for and the interest rate on cash and liquid assets, respectively. In addition, x_t^h is decreasing in R_t, interest on risk-free bonds, due to a substitution effect, and decreasing in λ_t, the multiplier of the budget constraint, due to a wealth effect.

Firms

Firms' problem coincides with the partial equilibrium model presented in Section 1.2.1 properly augmented with pricing and production decisions. Firms' side is characterized by a continuum of monopolistically competitive firms $i \in [0, 1]$ producing a differentiated variety of goods with the following production function:

$$y_{i,t} = \left(\frac{A_t}{a_{i,t}} n_{i,t} \right)^{\alpha} - \phi; \quad 0 < \alpha \leq 1 \text{ and } \phi > 0. \tag{1.5}$$

As before, A_t is aggregate productivity and $a_{i,t}$ is the idiosyncratic productivity level, which follows the log-normal distribution $\log a_{i,t} \sim N(-0.5\sigma_a^2, \sigma_a^2)$. In addition, parameter α governs the degree of decreasing returns of labor input $n_{i,t}$ and ϕ is a common fixed cost of production.

Following Kiley and Sim (2014) and Gilchrist et al. (2017), firms make pricing $p_{i,t} = P_{i,t}/P_t$, production $y_{i,t}$, and saving (corporate cash and liquid assets) $x^f_{i,t} = X^f_{i,t}/P_t$ decisions after observing aggregate shocks but before observing idiosyncratic productivity $a_{i,t}$. After committing to those decisions, idiosyncratic productivity $a_{i,t}$ is revealed and firms hire labor $n_{i,t}$ to meet demand $c_{i,t}$ such that $y_{i,t} = c_{i,t}$. Analogously to the model presented in Section 1.2.1, the value of $a_{i,t}$ can be such that (real) dividends $d_{i,t}$ are strictly less than zero and, in this case, firm i faces the dilution cost φ_t which implies that the actual flow from the issuance is reduced by $\varphi_t d_{i,t}$. This timing convention –together with the assumption of $a_{i,t}$ to be i.i.d. across firms and over time– implies that firms are always identical at the beginning of the period and that dividends $d_{i,t}$ and labor input $n_{i,t}$ are functions of the idiosyncratic level $a_{i,t}$.

Analogously to the definition of dividends in Section 1.2.1, the flow-of-funds constraint is

$$\begin{aligned} d_{i,t} = p_{i,t}c_{i,t} - w_t n_{i,t} - \frac{\gamma_p}{2}\left(\pi_t \frac{p_{i,t}}{p_{i,t-1}} - \pi_{ss}\right)^2 c_t \\ + \frac{R^x_{t-1}}{\pi_t} x^f_{i,t-1} + g(x^f_{i,t-1}/\pi_t) - x^f_{i,t} + \varphi_t \min\{0, d_{i,t}\}. \end{aligned} \tag{1.6}$$

Relatively to its partial equilibrium counterpart, Equation 1.6 is augmented with pricing $p_{i,t}$, production $c_{i,t} = y_{i,t}$, and input $n_{i,t}$ decisions, together with nominal rigidities à la Rotemberg (1982). In addition, $\pi_t = P_t/P_{t-1}$ is current inflation, R^x_{t-1} is the nominal interest rate on previous period cash and liquid assets, and $g(\cdot)$

is a positive, increasing, and concave function which captures the benefits of the financial flexibility associated with the stock of cash.

The firm's objective is to maximize the expected present value of dividends,

$$\max_{d_{i,t}, n_{i,t}, c_{i,t}, s_{i,t}, p_{i,t}} \mathbb{E}_0 \left[\sum_{t=0}^{\infty} m_t d_{i,t} \right],$$

where m_{t+1} represents the stochastic discount factor set by the households, subject to: (i) the production function presented in Equation 1.5; (ii) the flow-of-funds constraint presented in Equation 1.6; (iii) habit-augmented good-specific demand:

$$c_{i,t} = \left(\frac{p_{i,t}}{\tilde{p}_t} \right)^{-\eta} s_{i,t-1}^{\theta(1-\eta)} q_t;$$

and (iv) the law of motion of the habit stock $s_{i,t} = \rho s_{i,t-1} + (1-\rho) c_{i,t}$. See Appendix A.7.3 for derivations and optimality conditions.

Closing the model

I assume that the supply of nominal cash and liquid assets $\bar{X}_t$ is defined as follows

$$\bar{X}_t = (\bar{X}_{t-1})^{\omega_x} \left[\bar{x}_{ss} P_t \left(\frac{R_{ss}^x}{R_t^x} \right)^{\omega_r} \right]^{1-\omega_x}$$

where $\bar{x}_{ss}$ and R_{ss}^x represents the amount of and the interest rate on cash and liquid assets in steady state, respectively. In addition, parameters $\omega_x \in [0,1]$ and $\omega_r > 0$ govern the degree of persistence of cash and liquid assets, and the elasticity of $\bar{X}_t$ to its interest rate R_t^x, respectively. As a result, the real supply of cash and liquid assets $\bar{x}_t = \bar{X}_t/P_t$ can be expressed as follows,

$$\bar{x}_t = \left(\frac{\bar{x}_{t-1}}{\pi_t}\right)^{\omega_x} \left[\bar{x}_{ss}\left(\frac{R^x_{ss}}{R^x_t}\right)^{\omega_r}\right]^{1-\omega_x}. \tag{1.7}$$

Note that the real stock of cash has the consistent features to be a decreasing function of inflation π_t and of the nominal interest rate R^x_t. Moreover, if $\omega_x = \omega_r = 0$, then the real stock of liquid assets is perfectly inelastic and always equal to $\bar{x}_{ss}$; while if $\omega_x = 0$ and ω_r approaches infinity, then the real stock of money is perfectly inelastic and $R^x_t = R^x_{ss}$. In Section 1.5.4 I show that all the results are robust to any combinations of parameters ω_x and ω_r. Given the supply of cash, the market clearing that pins down R^x_t is,

$$\bar{x}_t = x^f_t + x^h_t,$$

where the left-hand side and the right-hand side represent the economy-wide supply and demand of cash and liquid assets, respectively.

The monetary authority set the nominal interest rate R_t following a standard Taylor rule,

$$R_t = R^{\rho_r}_{t-1}\left[R_{ss}\left(\frac{\pi_t}{\pi_{ss}}\right)^{\psi_\pi}\left(\frac{y_t}{y_{ss}}\right)^{\psi_y}\right]^{1-\rho_r}.$$

where R_{ss}, π_{ss}, and y_{ss} represent the steady state values of nominal interest rate R_t, inflation π_t, and output y_t, respectively. In addition, parameters ρ_r, ψ_π, and ψ_y govern the degrees of the policy inertia, inflation gap response, and output gap response, respectively.

In addition, I assume that the frictional costs of negative equity issuance and price adjustments, and all the benefits and costs associated with cash holdings are paid back to the households together with dividends d_t such that the resource constraint boils down to

$$c_t = y_t.$$

Finally, analogously to the partial equilibrium model presented in Section 1.2.1, an adverse financial shock is an unexpected increase in the dilution cost φ_t, and an uncertainty shock is a second-moment shock to future aggregate productivity A_{t+1}. The respective laws of motions of the exogenous processes are,

$$\log(\varphi_t/\varphi_{ss}) = \rho_F \log(\varphi_{t-1}/\varphi_{ss}) + \sigma^F \varepsilon_t^F,$$

$$\log(A_t) = \rho_A \log(A_{t-1}) + \sigma_{t-1}^A \varepsilon_t^A,$$

$$\log(\sigma_t^A/\sigma^A) = \rho_U \log(\sigma_{t-1}^A/\sigma^A) + \sigma^U \varepsilon_t^U,$$

where ε_t^F, ε_t^A, and ε_t^U are a financial shock, a technology shock, and an uncertainty shock, respectively. In addition, ρ_F, ρ_A, and ρ_U govern the persistence of the three processes, and σ^F, σ^A, and σ^U represent the variance of the three shocks.

1.5.2 Dynamics of corporate cash and inflation

Analogously to the partial equilibrium model presented in Section 1.2.1, the first order condition for corporate cash holdings is

$$1 = \mathbb{E}_t \left\{ \frac{m_{t+1}}{\pi_{t+1}} \frac{\xi_{t+1}}{\xi_t} \left[R_t^x + g'(x_t^f) \right] \right\}, \tag{1.8}$$

where ξ_t is the multiplier associated with the flow-of-funds constraint, and $R_t^x + g'(x_t^f)$ is the marginal benefit of holding cash at time $t+1$. Equation 1.8 mirrors Equation 1.1 with the only difference that the deterministic discount factor β is now substituted by m_{t+1}/π_{t+1} which is the stochastic discount factor divided by future inflation. This implies that the partial equilibrium intuition of cash holdings x_t^f as an insurance against the future risk of cash flow shortages is still in place. In particular, after a financial shock, the implicit cost of purchasing this insurance rises ($\uparrow \xi_t$) and firms opt for holding less of it, while, after an uncertainty shock, firms appreciate this insurance more ($\uparrow \xi_{t+1}$) and opt for holding more of it.

At this stage, it is more interesting to evaluate how general equilibrium forces affect firms' saving decisions after the two shocks. By replacing β with the stochastic discount factor m_{t+1} at the numerator and π_{t+1} at the denominator, I need to address how those two variables separately affect the right-hand side of Equation 1.8. In case of financial shocks, the stochastic discount factor decreases because households expect the effects of the contraction to die out in the near future; viceversa, in case of uncertainty shocks, the same variable increases due to the Jensen's inequality because households expect larger consumption variance in future. Thus, after a financial shock, households are more impatient and push firms to decrease savings, i.e. cutting corporate cash holdings, and distribute more dividends today. Conversely, after an uncertainty shock, households are more patient and push firms to increase savings in order to receive larger dividends in future for a precautionary motive.

Moreover, given the empirical result presented in Section 1.4 on inflation, let's consider the case where financial shocks are inflationary and uncertainty shocks are deflationary also in the model (I will explain why it is the case and confirm it with numerical simulations later on in this section). In the case of a financial shock, inflation is above its steady state level and the benefit of holding cash is now lower because, for a given interest rate R_t^x, the future purchasing power of cash is falling. As a result, firms have an additional incentive to draw down the stock of cash holdings. On the other hand, in the case of an uncertainty shock, inflation is below its steady state level and the benefit of holding cash is now higher because, given R_t^x, the purchasing power of cash is raising. Thus, uncertainty shocks push firms to invest in corporate cash holdings over this additional channel.[15] In addition, since the real supply of cash $\bar{x}_t$ is decreasing (increasing) after a financial (uncertainty) shock (see Equation 1.7), the fact that also households want to decrease (increase) cash holdings for an analogous reason does not particularly affect the analysis described here.[16]

[15] Note that this theoretical argument is in line with the empirical evidence by Curtis et al. (2017).

[16] From the optimality condition presented in Appendix A.7.2, households have analogous incentives on cash holdings when inflation is deviating from its steady state level. If the real stock of cash $\bar{x}_t$ would be constant, then the argument described in this paragraph would survive only if those

To understand why inflation has a qualitatively different response to financial and uncertainty shocks, let's focus on the optimality condition (after aggregation) for prices $p_{i,t}$:

$$\gamma_p\big(\pi_t - \pi_{ss}\big)\pi_t = \mathbb{E}_t\left[m_{t+1}\frac{\xi_{t+1}}{\xi_t}\gamma_p\big(\pi_{t+1} - \pi_{ss}\big)\pi_{t+1}\frac{c_{t+1}}{c_t}\right] - \eta\frac{\nu_t}{\xi_t} = 0,$$

that, as a first order approximation, leads to

$$\hat{\pi}_t = \beta\,\mathbb{E}_t\left[\hat{\pi}_{t+1}\right] + \tilde{\eta}(\hat{\xi}_t - \hat{\nu}_t) \tag{1.9}$$

where $\tilde{\eta} > 0$, ξ_t is the multiplier associated with the flow-of-funds constraint, and ν_t is the multiplier associated with the good-specific demand (see Appendices A.7.3 and A.7.4 for details). As already explained by Gilchrist et al. (2017), $\hat{\xi}_t$ has an inflationary effect because, given a larger need of internal resources ($\uparrow \xi_t$), firms' best response is to increase prices to generate additional liquidity from the customer base associated with the good-specific habit. In addition, $\hat{\nu}_t$ is an inverse function of the output gap and the larger is a contraction ($\downarrow y_t$), the lower is the good-specific demand ($\downarrow c_{i,t}$), and the larger the incentive to decrease prices ($\uparrow \nu_t$).

As a result, given future inflation expectations $\mathbb{E}_t[\pi_{t+1}]$, the response of inflation π_t to financial and uncertainty shocks depends on the response of $\hat{\xi}_t$ relative to $\hat{\nu}_t$. Intuitively, after a financial shock, the higher cost of external finance increases the

incentives were stronger for the firms than for the household. Nevertheless, since the real stock of cash $\bar{x}_t$ is moving in the desired direction (see Equation 1.7), this issue is not in place. In addition, as shown in Section 1.5.4, even if the real stock of cash is constant and equal to $\bar{x}_{ss}$ –which implies that this channel is potentially neutralized– the direction of corporate cash holdings after financial and uncertainty shocks is robustly preserved.

need to generate current internal liquidity ($\uparrow \xi_t$) relatively more than the fall in demand ($\uparrow \nu_t$), and firms would rather increase prices to avoid costly external finance. On the other hand, after an uncertainty shock, the need to generate current internal liquidity is not largely affected (since φ_t is unchanged, ξ_t is relatively stable), while the fall in demand ($\uparrow \nu_t$) for a precautionary motive encourages firms to cut prices. In addition, the fall in prices in response to an uncertainty shock has an inter-temporal effect which is more concealed and related to a precautionary motive. If firms decrease prices today, the good-specific demand and the stock of good-specific habit are increasing more (or decreasing less), which implies a larger increase (or smaller decrease) of the future customer base. Thus, after an uncertainty shock, firms are encouraged to cut prices also to increase the future customer base (which guarantees more future profits) for a precautionary motive against the heightened uncertainty.

1.5.3 Calibration and model simulations

In this section, I numerically solve the model in order to see if the economic intuitions described above hold for a set of reasonable parameterizations. Following Fernández-Villaverde et al. (2011) I solve the model to a third-order approximation of the policy functions in order to estimate the independent effect of a second-moment shock.[17] Moreover, following Basu and Bundick (2017) I analyze traditional impulse response functions in percent deviation from the stochastic steady state of the model. To obtain these responses, I set the exogenous shocks to zero

[17] I use the Dynare software package developed by Adjemian et al. (2011) to solve and simulate the baseline model.

and iterate the third-order solution forward until the model converges to a fixed point, i.e., the stochastic steady state.[18] Then, I hit the economy with a one standard deviation financial shock ε_t^F or uncertainty shock ε_t^U under the assumption that the economy is hit by no other shocks. I compute the impulse response functions as the percent deviation between the obtained responses and the stochastic steady state.

I calibrate the model to a quarterly frequency using steady-state relation on U.S. data or results from previous studies. In the baseline parameterization, I set β in order to match a 3% annual interest yield on bonds. The inverse of households' inter-temporal elasticity of substitution γ_q is equal to one, which implies log-utility in consumption. The multiplicative parameter in leisure χ_n is such that percentage of hours worked in steady state is equal to 0.3 while the multiplicative parameter in household cash holdings χ_x is such that the interest rate on cash and liquid assets R_t^s in steady state is equal to one. The good-specific habit parameter θ, the elasticity of substitution across differentiated goods i η, and the persistence of the habit stock ρ_s are -0.8 (Ravn et al., 2006; Gilchrist et al., 2017), 0.95 (Gilchrist et al., 2017), and 2 (Broda and Weinstein, 2006; Gilchrist et al., 2017), respectively. Following Gilchrist et al. (2017), the decreasing return to scale parameter α, the fixed cost of production ϕ, and the variance of the distribution of idiosyncratic productivity σ_a^2 are equal to 0.8, 0.3, and 0.05, respectively. The parameter that governs the cost of price ad-

[18] Other contributions refer to the stochastic steady state as the mean of the endogenous variables when simulating an infinity number of observations. The definition of stochastic steady state used here is in line with the one provided in the Online Appendix by Basu and Bundick (2017). In addition, the results presented here are robust to using the Generalized impulse responses around the ergodic steady state as described by Koop et al. (1996).

justment γ_p is equal to 10, which is in the range suggested by Ravn et al. (2006). The parameters ζ_x of the financial flexibility function of cash $g(x) = \zeta_x x^{1-\iota_x}/(1-\iota_x)$ is calibrated to match the empirical average of corporate cash holdings over total cash in the whole economy, while the parameter $\iota_x \in (0,1)$ is set equal to 0.5. The total amount of cash in steady state $\bar{x}_{ss}$ is calibrated to match the average empirical value of total cash over output. In the baseline calibration, persistence of total cash $\omega_x \in [0,1]$ and its elasticity to the related interest rate $\omega_r \geq 0$ are set equal to 0.5 and 1. In line with the standard New Keynesian literature, the monetary policy inertia ρ_r, the Taylor rule parameter on the inflation gap ψ_π, and the Taylor rule parameter on the output gap ψ_y are respectively 0.75, 2, and zero. Following Leduc and Liu (2016), persistence of technology shocks ρ_A is equal to 0.95; and, for a comparison, the persistence of financial shocks ρ_F and uncertainty shocks is ρ_U is equal to 0.9 in both cases. In addition, following Leduc and Liu (2016) variance of aggregate technology shocks σ^A and of uncertainty shocks σ^U is equal to 0.01 and 0.392, respectively; following Gilchrist et al. (2017), variance of financial shocks σ^F is equal to 0.075. Table 2.1 summarizes the baseline calibration.[19]

Figure 1.5 shows model-implied impulse responses to a financial shock and an uncertainty shock. In particular, Figure 1.5a displays responses to a financial shock that triggers a one percent decrease in output y_t. A financial shock has a contractionary effect on output y_t, consumption c_t, and hours n_t. Real wages w_t also fall due to a large decrease in the labor demand which is associated with a jump in

[19] All the parameters target values of the *deterministic* steady state since those values from the stochastic steady state are quantitatively analogous. In addition, values for ι_x, ω_x, and ω_r are given on an arbitrarily basis because results are robust to *all* the possible values that those parameters can take. See Section 1.5.4.

Table 1.4: Model's parameter values

Param.	Interpretation	Value	Objective
β	Discount factor	0.9926	$R_{ss} = 3\%$
γ_q	CRRA in q_t	1	Log-utility
χ_n	Utility from leisure	5.036	$n_{ss} = 0.33$
χ_x	Utility from liquidity	0.0143	$R^x_{ss} = 1$
θ	Habit parameter	-0.8	Ravn et al. (2006)
ρ_s	Habit stock persistence	0.95	Gilchrist et al. (2017)
η	Elasticity of substitution	2	Broda and Weinstein (2006)
α	DRS parameter	0.8	Gilchrist et al. (2017)
ϕ	Fixed cost	0.3	Gilchrist et al. (2017)
σ^2_a	Variance of $a_{i,t}$	0.05	Gilchrist et al. (2017)
γ_p	Price adj. cost	10	Ravn et al. (2006)
ζ_x	Financial flexibility (1)	0.0013	$x^f_{ss}/\bar{x}_{ss} = 0.116$
ι_x	Financial flexibility (2)	0.5	See robustness checks
$\bar{x}_{ss}$	Total cash in s.s.	0.2451	$\bar{x}_{ss}/y_{ss} = 2.176$
ω_x	Persistence of $\bar{x}_t$	0.5	See robustness checks
ω_r	Elasticity of $\bar{x}_t$ to R^x_t	1	See robustness checks
ρ_r	Monetary policy inertia	0.75	Standard NK literature
ψ_π	Taylor Rule on π gap	2	Standard NK literature
ψ_y	Taylor Rule on y gap	0	See policy experiment
ρ_F	Persistence of ε^F_t	0.9	Comparison with ρ_U
ρ_A	Persistence of ε^A_t	0.95	Leduc and Liu (2016)
ρ_U	Persistence of ε^U_t	0.9	Comparison with ρ_F
σ^F	Standard deviation of ε^F_t	0.075	Gilchrist et al. (2017)
σ^A	Standard deviation of ε^A_t	0.01	Leduc and Liu (2016)
σ^U	Standard deviation of ε^U_t	0.392	Leduc and Liu (2016)

Notes. β is the deterministic discount factor; γ_q is the constant relative risk aversion parameter in the consumption bundle γ_q; χ_n is the multiplicative parameter in household leisure; χ_x is the multiplicative parameter in household cash and liquid assets; θ governs the intensity of the external good-specific habit; ρ_s governs the persistence of the good-specific habit stock; η is the elasticity of substitution across differentiated goods i; α governs the decreasing return of labor input to total output; ϕ is the fixed cost of production; ς_a is the variance of the distribution of idiosyncratic productivity $a_{i,t}$; γ_p governs the price adjustment-cost; ζ_x is the multiplicative parameter of the financial flexibility function $g(\cdot)$; ι_x is the elasticity of the financial flexibility function $d(\cdot)$ to the argument; $\bar{x}_s s$ is the nominal and real stock of total cash and liquid assets in steady state; ω_x is the persistence of the nominal stock of assets $\bar{X}_t$; ω_r is the elasticity of the nominal stock of assets to its interest rate R^x_t; ρ_r governs the degree of inertia in the monetary policy response to the output gap and inflation gap; ψ_π governs the degree of response of the monetary policy to the inflation gap; ψ_y governs the degree of response of the monetary policy to the output gap; ρ_F and σ^2_F are the persistence and the variance of financial shocks ε^F_t; ρ_A and σ^2_A are the persistence and the variance of technology shocks ε^A_t; ρ_U and σ^2_U are the persistence and the variance of uncertainty shocks ε^U_t.

markup μ_t, defined as the inverse of the real marginal cost (see Figure 1.7 for the response of the markup μ_t). As suggested by the qualitative analysis in Section 1.5.2, inflation π_t jumps on impact because the shadow value of boosting internal resources ξ_t increases more than the shadow value of attracting new demand $\nu_{i,t}$. As suggested by the quantitative analysis in Section 1.2.1 and the qualitative analysis in Section 1.5.2, corporate cash holdings x_t^f falls by a large amount in order to substitute the costly external finance with internal resources. Both the rise in inflation and the fall in consumption encourage the households to cut investment in cash and liquid assets and, as a general equilibrium effect, the interest rate on cash and liquid assets R_t^x increases. Along those lines, the real supply of cash and liquid assets $\bar{x}_t$ increases consistently with the empirical results presented in Figure 1.2 in Section 1.4. Finally, the policy rate set by the monetary authority R_t rises, rather than decreasing, because the output gap parameter ψ_y is currently equal to zero. This result is fairly in line with the empirical results where the federal funds rate is mostly not significant or mildly decreasing in face of a financial shock.

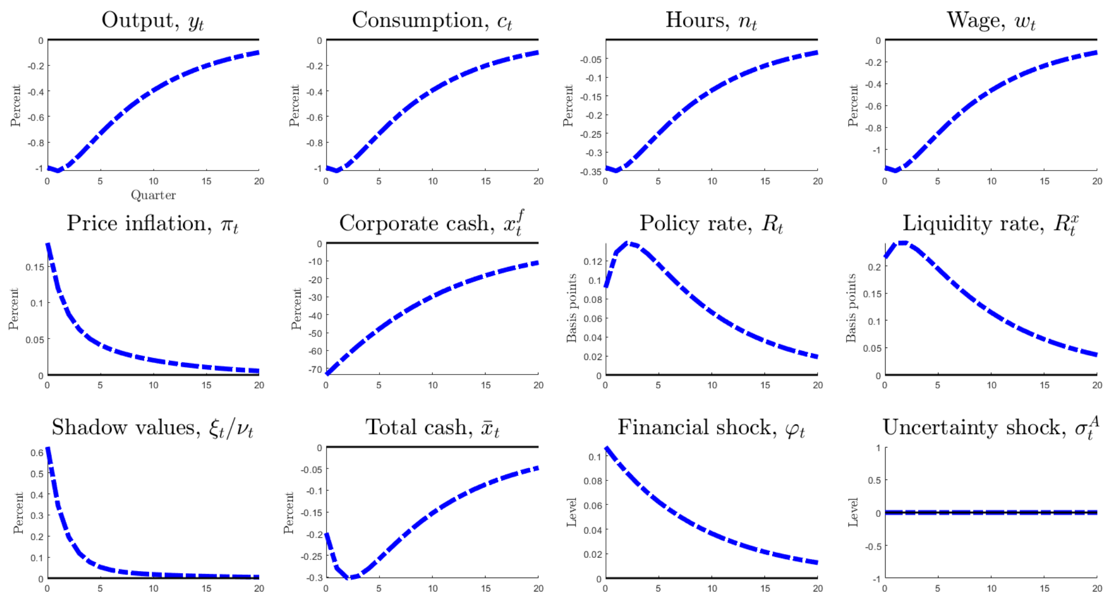
Figure 1.5b displays responses to an uncertainty shock that triggers a one percent decrease in output y_t. Analogously to a financial shock, also uncertainty shocks have a contractionary effect on output y_t, consumption c_t, hours n_t, and real wage w_t due to the decrease in labor demand associated with an increase in markup μ_t (see, also in this case, Figure 1.7 for the response of markup μ_t). Contrary to a financial shock, uncertainty shocks are associated with deflationary forces since in this case the shadow value of generating internal resources ξ_t increases less than the shadow value of attracting new demand $\nu_{i,t}$. Moreover, in line with the arguments and results provided in previous sections, corporate cash holdings x_t^f increases in order to cushion the larger future risk associated with the heighten uncertainty. The fall in inflation and a precautionary motive encourage the households to investment more in cash and liquid assets with the result that the interest rate R_t^x decreases. As a result, the real supply of cash and liquid assets $\bar{x}_t$ increases consistently with the empirical results presented in Figure 1.2b. In addition, in face of an uncertainty shock, the policy rate R_t falls as a device to close the inflation gap qualitatively matching the empirical results presented in the Section 1.4.

1.5.4 Robustness

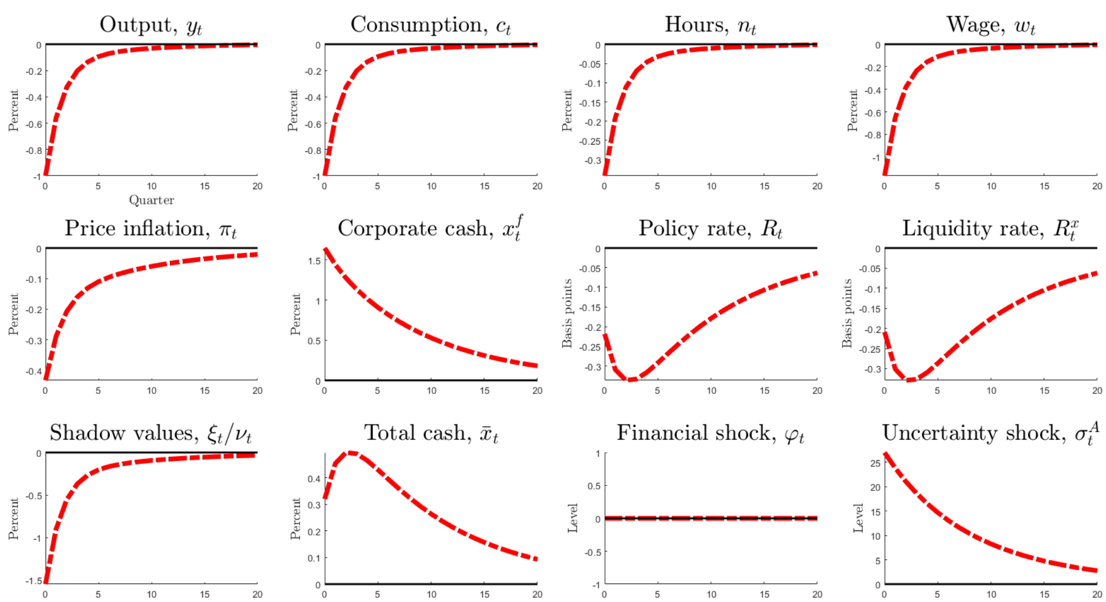
In this section, I show a series of robustness checks to confirm that the qualitative implications presented in Figure 1.5 are robust to different parameterizations. Figure 1.6 presents various responses to inflation π_t and corporate cash holdings x_t^f to a financial and an uncertainty shock that trigger a one percent contraction in output y_t. Each subplot displays the response for the baseline calibration (solid line), for a calibration that decreases the value of one (or two) parameter(s) (dashed line), and for a calibration that increases the value of the same parameter(s) (dotted line) relatively to the baseline calibration. I show five robustness checks. The subplots presented in the first column show responses to different values of the inverse of households' inter-temporal elasticity of substitution γ_q. The values are one third, one, and two for the lower value, the baseline, and the higher value, respectively. The second column is associated to changes in the good-specific habit parameter θ; values are -0.5, -0.8, and -1.5 for the lower absolute value, the baseline, and the higher absolute value. The third column is related to changes in the parameters that govern the price adjustment costs; values are one, 10, and 50 for the three cases. The fourth column show responses associated with calibrations that affect

Figure 1.5: Model-implied impulse responses

(a) Financial shocks



(b) Uncertainty shocks



Notes. Model-implied responses to a financial shock and an uncertainty shock whose size trigger a one-percent contraction in output. Model's parameter values are presented in Table 2.1.

the supply of cash and liquid assets $\bar{x}_t$ as presented in Equation 1.7. The lower value means $\omega_x = \omega_r = 0$ which implies a perfectly inelastic real cash supply, such that $\bar{x}_t = \bar{x}_{ss}$ in every period; while, the higher value means $\omega_x = 0$ and ω_r approaching infinity which implies a perfectly elastic cash supply, such that $R_t^x = R_{ss}^x$ in every period. Finally, the last column is associated with different values of the parameters $\iota_x \in (0,1)$, that governs the elasticity of financial flexibility $g(\cdot)$ to changes in corporate cash x_t^f. Values are 0.01, 0.5, and 0.99 for the lower case, the baseline, and the higher case, respectively.

The qualitative result on output y_t, consumption c_t, hours worked n_t, and real wage w_t are implicitly confirmed since the the responses displayed in Figure 1.6 are associated with a one percent contraction in output.[20] Moreover, in all cases, the qualitatively different responses of both inflation π_t and corporate cash x_t^f to financial and uncertainty shocks are preserved across all the robustness checks. This suggests that the results presented in the baseline are not implied by a specific combination of parameter values but are mostly implied by the structure of the model as discussed in Section 1.5.2.

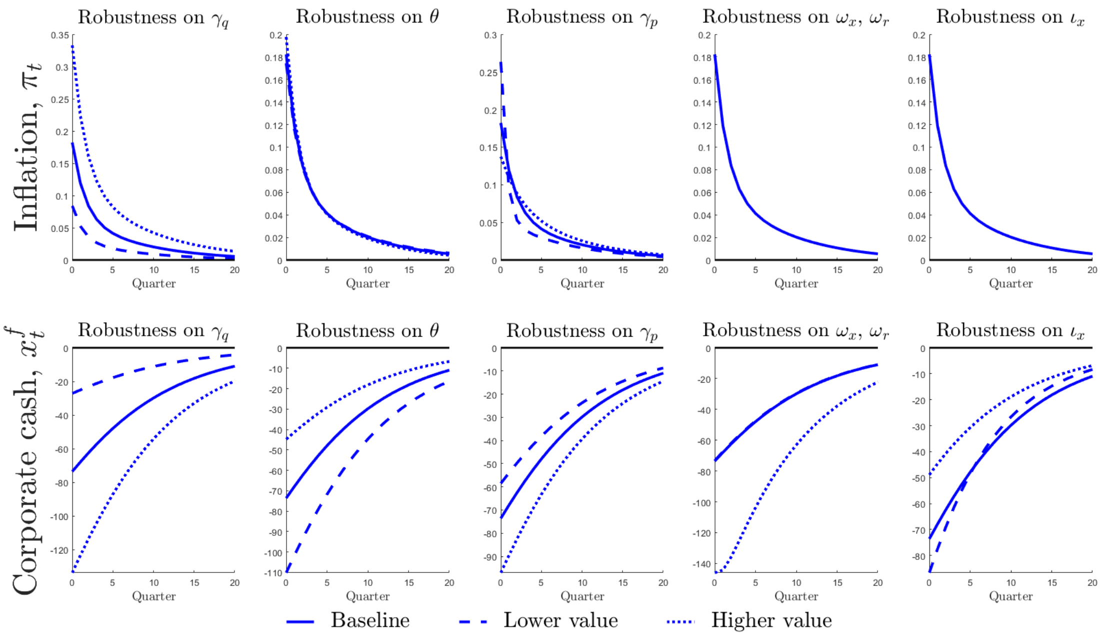
1.5.5 Monetary policy implications

According to the empirical and model-implied responses, financial shocks move inflation π_t and output y_t in two different directions, while uncertainty shocks move these two variables in the same direction. This difference is the key reason why being able to disentangle financial shocks from uncertainty shocks is of primary importance for monetary policy. In case of uncertainty shocks, the positive comovement between output and inflation suggests that the divine coincidence is in place

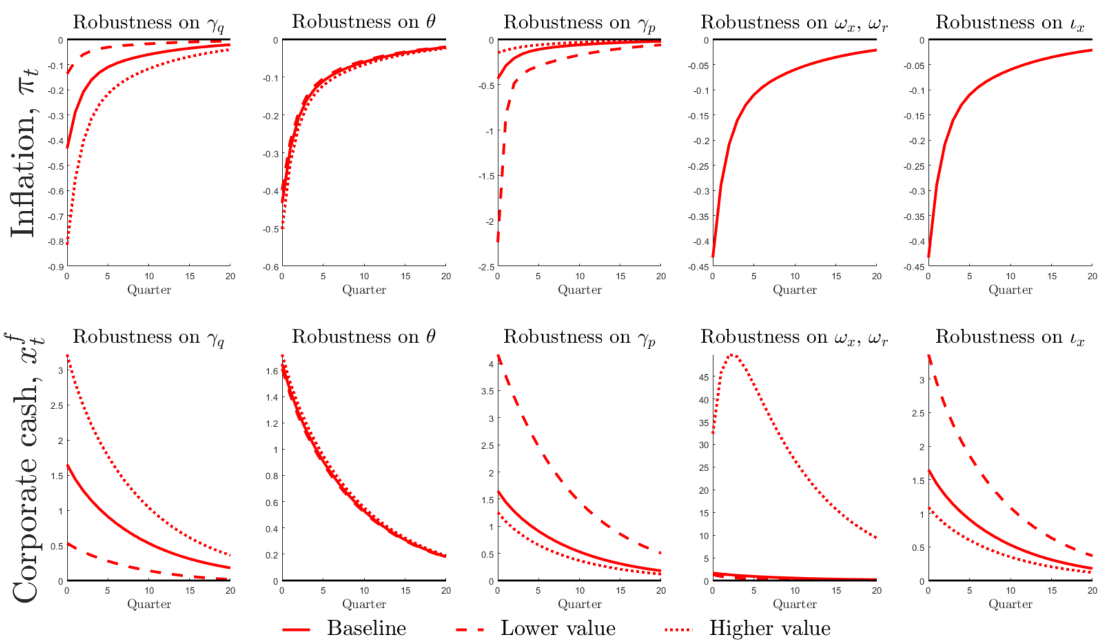
[20] If output y_t decreases then also c_t (equal to y_t) and n_t (proportional to y_t) have to fall. The decrease in real wage w_t, instead, depends on the fact that the labor supply increases (due to a wealth effect) and the labor demand decreases (due to the counter-cyclical markup) implying necesserely a fall in the real wage.

Figure 1.6: Robustness checks on model-implied impulse responses

(a) Financial shocks

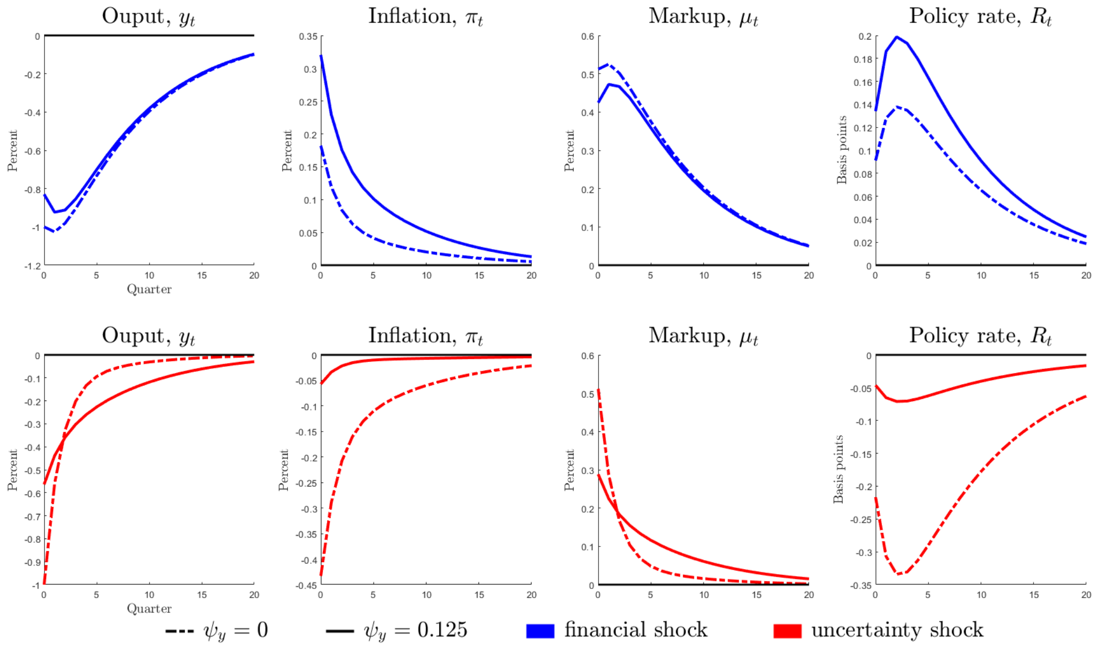


(b) Uncertainty shocks



Notes. Model-implied responses to a financial shock and an uncertainty shock whose size trigger a one-percent contraction in output in the baseline calibration. Responses are obtained from different calibrations.

Figure 1.7: Monetary policy experiment on Taylor rule parameter ψ_y



Notes. Model-implied responses to a financial shock and an uncertainty shock whose size trigger a one-percent contraction in output in the baseline calibration. Responses are obtained using different values of the output gap coefficient ψ_y.

and the monetary policy can simultaneously close the output gap and the inflation gap. Conversely, the negative comovement between output and inflation after a financial shock suggests the existence of a non-trivial trade-off between output and inflation for the monetary policy.

In order to formally explore those implications, I examine the two contractions presented in Figure 1.5 by allowing monetary policy also to respond to the output gap, i.e., $\psi_y > 0$. Figure 1.7 shows responses of output y_t, inflation π_t, markup μ_t, and policy rate R_t to a financial shock (top row) and uncertainty shock (bottom row). Each subplot presents two responses: the dashed line refers to the baseline presented in Figure 1.5 ($\psi = 0$) and the solid line is obtained from a new calibration where, as a policy experiment, the monetary authority also responds to the output gap ($\psi = 0.125$).

As shown by the differences in the responses, increasing the coefficient associated with the output gap ψ_y successfully stabilize output y_t both in the case of financial shocks and uncertainty shocks. Nevertheless, in the case of uncertainty shocks, the stabilization of the output gap is followed by an even further stabilization of the inflation gap; while, in the case of financial shocks, the monetary authority can stabilize the output gap only at the cost of higher inflation. In my model, therefore, the divine coincidence holds only for uncertainty shocks, and, after a financial shock, the monetary authority has to balance its intervention between the output gap and the inflation gap.

1.6 Conclusions

This paper shows that there exist two distinct sources of business cycle fluctuations that both associated with higher uncertainty and wider credit spreads. Beyond the labeling of financial and uncertainty shocks, corporate cash holdings can be useful to understand how much an economic contraction is inherent to the financial sector or to the uncertainty associated with the real economy. With the help of a new econometric strategy, empirical results suggest that financial shocks explain almost 40% of output fluctuations over a business cycle frequency, while uncertainty shocks explain roughly 15%. In addition, two thirds of the Financial Crisis can be attributed to uncertainty shocks, while only a third of it can be attributed to financial shocks.

Finally, financial shocks are associated with inflationary forces, while uncertainty shocks are related to deflationary patterns.

I rationalize previous results in a tractable New Keynesian model with financial frictions, good-specific habits, and a market for cash and liquid assets. Counterfactual experiments show that the monetary authority deals with different challenges in face of the two shocks making the case undoubtedly interesting for policy implications. I find that in case of uncertainty shocks, the divine coincidence is in place and the monetary authority can simultaneously close the output gap and the inflation gap without any trade-offs. Conversely, in case of adverse financial shocks, the central bank can close the output gap only at the cost of higher inflation.

Chapter 2

What are the Sources of Boom-Bust Cycles?

2.1 Introduction

This paper provides a synthesis of two major views on economic fluctuations. One view maintains that expansions and recessions arise from the interchange of positive and negative persistent exogenous shocks to fundamentals. This is the conventional view that gave rise to the proliferation of shocks embedded in modern dynamic stochastic general equilibrium (DSGE) models. A second view, which we call the endogenous cycles view, holds that business cycle fluctuations are due to forces that are internal to the economy and that favor recurrent periods of boom followed by an *endogenous* bust. In this environment, cycles can occur even in absence of shocks to fundamentals. Conclusive evidence in favor of either view is hard to find. One reason may be that a complete representation of the economy is one in which both views coexist.

We make three contributions. First, we document a data conundrum that stems from contrasting unconditional and conditional evidence on the presence of endogenous cycles. We build on Beaudry et al. (2019, BGP henceforth) who provide compelling evidence that U.S. macroeconomic aggregates tend to move in regular cycles. We ask whether fundamental sources of fluctuations, such as technology shocks, can explain the regular cyclicality present in the data. We find that fundamental-driven expansions do not feature predictable future recessions and therefore fundamental shocks cannot account for the unconditional moments documented by BGP. Second, we build a theory that rationalizes the conundrum and proposes shocks to expectations as the key source of boom-bust cycles. According to our theory, positive shocks to expectations, such as waves of optimism, generate periods of boom that are *endogenously* followed by a recession. In contrast, expansionary fundamental shocks do not generate predictable busts. Thus, our theory provides new discipline for both the conventional view of exogenous cycles *and* the more heterodox view of endogenous cycles, by restricting their domain of application to fundamental shocks or to expectation shocks, respectively. Third, we identify expectation shocks using survey data from the U.S. and verify that, indeed, expectations shocks (i) generate predictable boom-bust episodes, (ii) bring about economic dynamics quantitatively consistent with our model, and (iii) account for a sizeable fraction of business cycle fluctuations.

In the first part of the paper, we begin by documenting the presence of a systemic cyclical behaviour in economic aggregates. We do so in two ways. First, we show that the spectral densities of a number of U.S. macroeconomic and financial variables display a peak at periodicities of around 8 to 10 years. A hump-shaped spectral density signals the presence of periodic motions that repeat themselves in a regular cycle. Second, we show that the probability of a recession peaks about two years after an expansion – findings that are *inconsistent* with the predictions of standard DSGE models. Next, we argue that the responses to identified fundamental shocks almost always deliver mean-reverting responses more aligned with the conventional view. We take a temporary shock to utilization-adjusted TFP as the leading case. A positive TFP shock leads to a temporary expansion that is not systematically followed by a recession. By comparing the conditional spectral densities implied by a TFP shock with their unconditional counterparts, we show that these shocks cannot be responsible for the cyclical properties of the data.

The presence of systemic cyclicality that is not due to fundamental shocks poses a conundrum. In the second part of the paper, we propose a general equilibrium model that rationalizes such conundrum. Given the particularly pronounced evidence of cyclical behaviour among financial variables, we place financial frictions at the hearth of our theory. The structure of the model echoes Jermann and Quadrini (2012) in that there are firms who borrow from households by issuing short- and long-term debt. Short-term debt is in the form of an intra-period working capital loan and therefore it is used to finance production inputs. For simplicity, we assume that the long-term debt is in the form of a one period bond that firms issue to smooth out dividends. The central innovation of the model is a default-deterring borrowing constraint that depends positively on firms' market value.

The endogenous borrowing limit has two important features. First, it introduces a pecuniary externality as firm's market value, defined as the discounted cumsum of its future cash flows, depends upon two components: firm's future profits which are under the direct control of the firm, and households' stochastic discount factor which the single firm takes as given. Second, it generates strong financial amplification due to a positive feedback loop between firms' market value and households' income. These two features combined make the model economy display boom-bust episodes. Crucially, busts arise endogenously after expansions led by positive shifts in agents' expectations, but not after expansions due to positive shocks to technology.

The intuition is as follows. Suppose that households become more optimistic regarding firms' future value so that equity prices increase. Increased equity prices relax borrowing constraints and allow firms to issue more short- and long-term debt. Since short-term debt is useful to finance production, looser borrowing constraints raise firms' demand for labor. The resulting higher wages increase households' labor income, their willingness to save, thereby leading to a further increase equity prices, and a relaxation of borrowing constraints. Therefore, an expectation-driven expansion features increasing equity prices, wages, debt, and output, due to a positive feedback loop between firms' market value and households' income. Crucially, the increase in equity prices is due to higher households' stochastic discount factor, and *not* to a change in firms' future profits. In fact, increased borrowing capacity increase wages which reduce firms' marginal profits and may lead to a profits *decline* over the expectation-driven expansion. As the economy evolves, lower firms' profitability distorts firms' incentives in such a way to trigger a recession. From the perspective of a single firm, lower profitability reduces its incentives to allocate borrowing capacity into working capital. However, firms fail to internalize that by hiring less input, households will receive less labor income, commanding a fall in equity prices and tighter borrowing constraints.

Intuitively, the amplification channel should deliver similar boom-bust responses after shocks to technology, but it does not. The reason is that equity prices increase primarily because of the increase in firms' profits thanks to higher productivity. Because of the increased profitability, firms will allocate funds predominantly to hire more inputs until the shock is absorbed, and, as a consequence, the distortion coming from the pecuniary externality will be less important.

We argue that changes in expectations distinct from changes of technology can rationalize the boom-bust features of the data, but what triggers such changes? The model's answer is that equilibrium outcomes are the product of self-fulfilling shifts in agents' expectations, and when these changes are unrelated to fundamentals they generate boom-bust dynamics. The intuition is that boom-bust dynamics obtain when the internal financial amplification channel is sufficiently strong, but this happens *only* in the case in which the dynamic equilibrium is indeterminate, that is, the economy is subject to self-fulfilling shifts in expectations (a.k.a. sunspots).

In the third part of the paper, we empirically identify expectation shocks and test the predictions of the model. Specifically, we construct an indicator that summarizes the revisions of expectations on the future economic outlook using quarterly data on expectations from the Survey of Professional Forecasters and the Survey of Consumers. We use the indicator to identify exogenous shifts in expectations that are uncorrelated with past, present and future realizations of TFP. In addition, we control for a number of leads and lags of shocks to expectations of TFP in order to isolate shifts in expectations that are pure sentiments from those originating from beliefs on future TFP. Using local projections, we find that expectation shocks generate significant boom-bust dynamics in all the aggregate variables that we examine, and explain up to 40% of real GDP at business cycle frequencies, consistent with the findings of Angeletos et al. (2018) and Chahrour and Ulbricht (2019).

Finally, we show that the mechanism of the model is consistent with many features of the data. First, we find that the model is able to reproduce the empirical impulse responses to both expectation and TFP shocks. As in the model, expectation shocks bring about a countercyclical movement of the labor wedge, while the labor wedge *increases* after TFP improvements. Second, we show that the model can replicate the reduced-form evidence on boom-bust cycles that motivated our analyses. Unlike standard business cycle models, our theory can explain both the hump in the spectral densities of macroeconomic and financial variables, and the rising probability of a recession during an expansion.

Related literature. This paper lies at the intersection between the strand of the finance literature that focuses on credit cycles and the broad macroeconomic literature that aims at understanding the sources of business cycles.

The idea that the financial system is prone to generate economic instability through endogenous credit booms traces back at least to Kindleberger (1978) and Minsky (1975,1986). Minsky (1986) provides groundbreaking insights on the relation between the economic and the financial system. Of particular interest for this paper is his distinction between "periods of tranquility," defined as situations during which the economy is not subject to disruptive changes, and "unstable times" during which market forces lead to a rise of financial instability which culminates in "speculative frenzies". Through the lenses of our model and empirical evidence, we view such "periods of tranquility" as moments during which technological changes are the major contributor to economics fluctuations, whereas "unstable times" are characterized by economic fluctuations primarily driven by changes in market expectations.

More recently, the idea that an increase in credit associated with a decrease in borrowing costs can be a powerful predictor of future economic crises has been empirically tested and verified using both macro and micro level data. For example, Schularick and Taylor (2012) and Jordà et al. (2013), using data on 14 developed countries from 1870 to 2008, demonstrate that rapid credit expansions forecast declines in real activity.[1] Using data on the credit quality of corporate debt issuers, Greenwood and Hanson (2013) find that a high share of risky loans tends to forecast low corporate bond returns. Krishnamurthy and Muir (2017) show that crises are preceded by a period of high credit to GDP growth and leverage, and low spread and risk premium. We complement this literature by providing conditional evidence

[1] Other examples include Demirgüç-Kunt and Detragiache (1998), Hardy and Pazarbasioglu (1998), Kaminsky and Reinhart (1999), Gourinchas et al. (2001), Goldfajn and Valdes (2006), Borio and Drehmann (2009), Reinhart and Rogoff (2009), Claessens et al. (2011), Gourinchas and Obstfeld (2012), and Laeven and Valencia (2013).

on the link between a credit boom and the ensuing recession. We show that positive expectation shocks - but not TFP shocks - are systematically followed by a recession. Our evidence on expectation shocks also relates to López-Salido et al. (2017) who focus on credit market sentiment identified using credit spreads and find that high credit market sentiments are a predictor of future negative output growth. We complement their analysis by showing that sentiment shocks not only predict a negative output growth but also prolonged periods during which the *level* of output is below trend.

We relate to the literature that aims at rationalizing boom-bust phenomena. For example, Boissay et al. (2016) rationalize boom-bust episodes in a model where the increase in households' savings during a boom exacerbates adverse selection problems in the interbank market. In our model, the increase in savings brings about a recession because it reflects an increase in firms' debt which tightens financial markets. A subset of this literature builds model of chaos and limit cycles. Boldrin and Woodford (1990) survey the literature and analyze the conditions under which limit cycles can emerge. In a recent paper, Beaudry et al. (2019) revisit the reduced-form evidence on the spectral densities of a series of economic variables. They build a model of limit cycles where small exogenous shocks give rise to perpetual economic cycles. While our model can also exhibit limit cycles for regions of the parameter space that imply a sufficiently tight financial constraint, our aim is rather to rationalize the fact that only a subset of shocks trigger oscillatory dynamics while other shocks do not. Gorton and Ordonez (2016) distinguish between “good" and “bad" credit booms depending whether or not they end up in a crisis.

They find that shocks in the trend of productivity are associated with "good" credit booms, whereas "bad" booms are typically associated with a decline in productivity. We differ from them in at least two aspects. First, we look at cycles at short and medium-run frequencies while their focus is on booms that last ten years on average. Second, we emphasize that the shocks responsible for boom-bust episodes are orthogonal to movements of TFP.

Furthermore, we relate to the class of models that generate self-fulfilling rational expectations equilibria due to credit market amplification. Examples of this class are Benhabib and Wen (2004), Benhabib and Wang (2013), Liu and Wang (2014), and Azariadis et al. (2015). While their emphasis is on a single shock, our model is built to capture the important different responses to fundamental and sunspot shocks.

Lastly, our theoretical framework shares some similarities with models of stock market bubbles as in Miao and Wang (2018), in that, debt limits depend upon firms' market value and sentiment shocks can be interpreted as bubbles. However, models of stock market bubbles formalize the burst of a bubble as an exogenous event. In contrast, in our model sentiment shocks rationalize both the formation of a bubble and its subsequent burst.

2.2 The *cyclicality* conundrum

Boom-bust cycles are a recurrent feature of the data. Yet, there is virtually no evidence of boom-bust dynamics conditional on shocks. We refer to such incoherence between unconditional and conditional evidence as the *cyclicality* conundrum. This section documents the conundrum by showing that (i) there is a systemic cyclical component in the data and (ii) shocks to fundamentals do not impart economic dynamics that can account for such systemic cyclicality.

2.2.1 Unconditional evidence of cycles

In a recent article, Beaudry et al. (2019) find that U.S. business cycles are characterized by cyclical forces. In particular, they show that the spectral densities of a number of economic aggregates exhibit a common local peak at periodicities of 32 to 50 quarters. The spectral density is a useful diagnostic tool of cyclicality for two reasons.[2] First, a peak in the spectral density signals the presence of oscillatory dynamics in the autocovariance function of the data. Second, it tells us whether these oscillatory dynamics happen at business cycle frequencies or they reflect lower frequency forces unrelated to business cycles.

Figure 2.1 reports the spectral density of a series of macroeconomic and financial variables.[3] We use quarterly data from 1967:q1 to 2018:q4 and detrend variables using a band pass filter that removes fluctuations with periodicities longer than 100 quarters.[4,5] Two patterns emerge. First, results point at the presence of a strong common cyclical component. With the exception of utilization-adjusted TFP, all variables exhibit a peak in the spectral density in the interval between 32 and 50 quarters. Furthermore, the fact that there are no notable differences in the shape of

[2] The notion of cyclicality that we use is analogous to Beaudry et al. (2019), that is a series is cyclical if its autocovariance function displays oscillations.

[3] The spectral density is computed using the Schuster's periodogram.

[4] Because filtering the series could induce a spurious hump in the spectral density, we check that results are robust to various detrending techniques and frequency bands.

[5] The choice of the data sample does not affect the results. We start from 1967 as it is consistent with the longest data sample available for the analyses carried in Section 2.4.

the spectral density across variables, suggests the presence of an underlying mechanism responsible for the cyclical patterns rather than idiosyncrasies in the variables examined. Second, financial variables exhibit a more pronounced peak relative to macroeconomic variables suggesting that the cyclical features of the data might originate from shocks propagating through the financial sector, whereas shocks that primarily hit the real sector of the economy generate less oscillatory dynamics.

Importantly, a hump-shaped spectral density is a finding inconsistent with the predictions of standard business cycle models. In Figure **??** in appendix B.2 we run a Monte Carlo simulation on the spectral density of output using a textbook Real Business Cycle model and the New-Keynesian model by Smets and Wouters (2007). We find that the spectral density of output from model simulated data is counterfactually increasing in the periodicity.

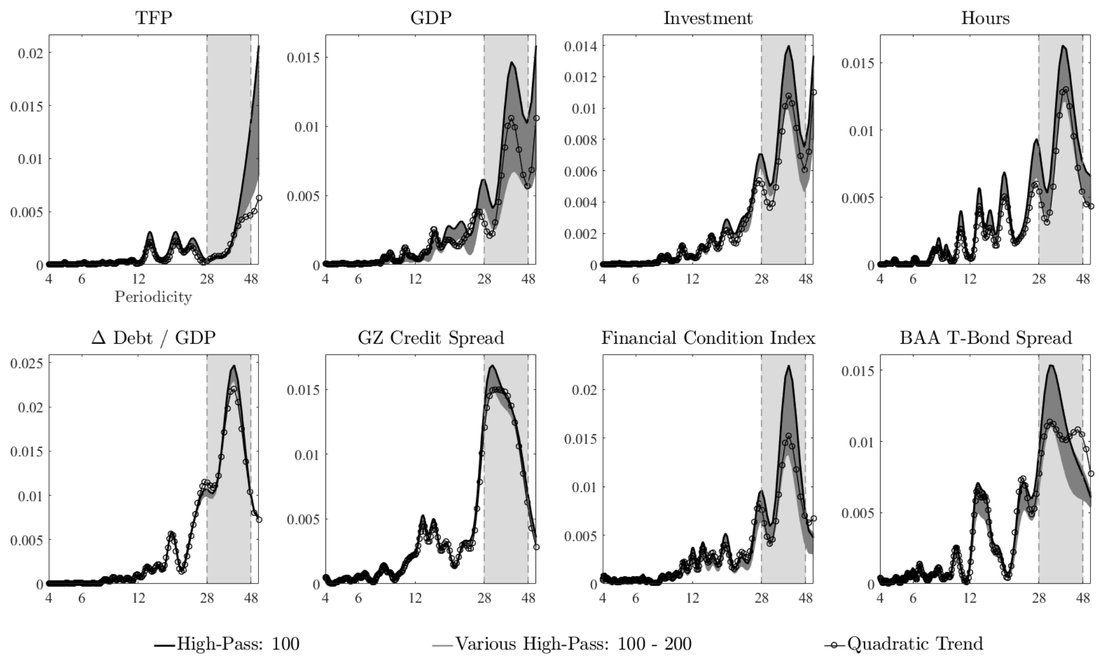


Figure 2.1: Unconditional spectral densities of quarterly U.S. signal systemic cyclicality

Note: Data from 1967:q1 to 2018:q4. TFP is utilization-adjusted total factor productivity. GDP is real gross domestic product. Investment is real consumption of durables plus real gross private domestic investment. Hours is hours of all persons in non-farm business sector. Change in debt is the flow of nonfinancial business debt securities and loans. GZ Credit Spread is the measure of credit spread described in Gilchrist and Zakrajšek (2012). Financial Conditions Index is provided by Chicago Fed. BAA T-Bill Spread is the difference between the yield of BAA corporate bonds and the treasury note at 10-year horizon. Series are detrended using a quadratic trend (circle-solid line), a filter that excludes fluctuations of period greater than 100 (black line), or from 101 to 200 (dark grey lines).

The presence of a systemic cyclical component in the data implies that the probability that a recession occurs should increase after an expansion. To verify whether this is true, we estimate a linear probability model and compute the probability that the economy enters in a recessions after k quarters since the previous expansion. We define expansions as periods in which real GDP growth is above the top quintile for at least two consecutive quarters. Likewise, we construct a recession indicator that takes value equal one if the real GDP growth falls into the bottom quintile for at least two consecutive quarters. Figure 2.2 plots the probability that the economy will be in a recession in a two-quarter window around time $t+k$ given an expansion at time t. Results confirm the evidence of cyclicality described above. The conditional probability of a recession increases after an expansion and peaks approximately after two years. The picture also shows the prediction from data simulated using standard business cycle models such as the one described in Smets and Wouters (2007), the textbook Real Business Cycle model. In addition, we run the same experiment using the incomplete information model of Blanchard et al. (2013). All models predict that recessions are effectively unforecastable, in that the probability of a recession quickly converges to its unconditional mean after an expansion. To see this, we plot the results from simulating a random walk process in levels and show that the results from all models considered are indistinguishable from the predictions obtained after simulating a random walk for real GDP.

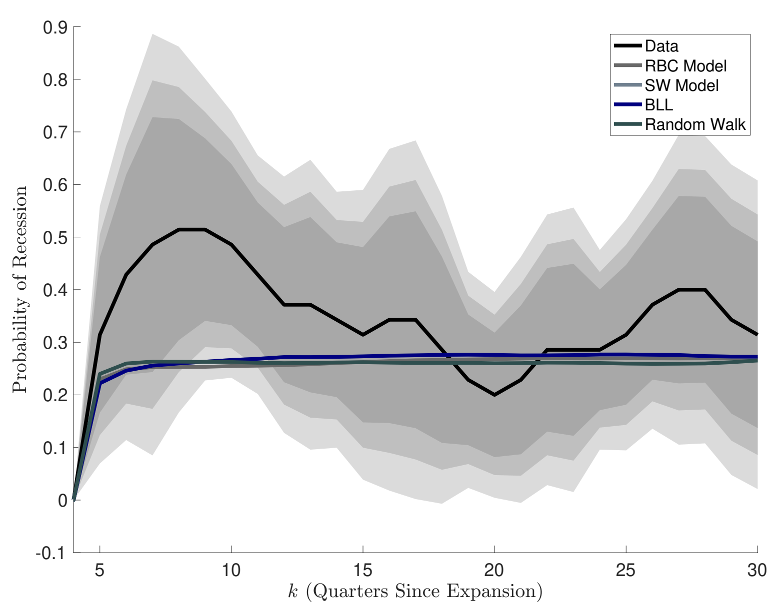


Figure 2.2: Probability of a recession peaks two years after an expansion

Note: Probability of recession in a two-quarter window after k quarters since expansion. Confidence intervals are 68%, 80%,and 90% (shaded areas) around the point estimate (solid black line).

2.2.2 Conditional rejection of cycles

Ultimately, we are interested in understanding the *sources* of the oscillatory behaviour documented above. To this end, we ask whether technology shocks account for these empirical regularities. We use quarterly utilization-adjusted TFP (Basu et al., 2006) and identify technology shocks as the innovation of detrended TFP after regressing it on its own lags, lags of the first principal component of a large dataset of aggregate economic variables and news shocks estimated following Barsky and Sims (2011).[6] We estimate impulse responses using the method of local projections proposed by Jordà (2005). Specifically, we estimate the h-th coefficient of the impulse response function by regressing each variable at time $t + h$ on the shock at time t.[7] We choose to implement the method of local projections because unlike vector autoregressions (VAR), it does not require to specify the lag structure of the data generating process.

[6] Results are robust to different detrending techniques, additional controls, and different number of lags and principal components. See Appendix B.3 for results and additional details.
[7] Details on local projections are in the Appendix B.5.

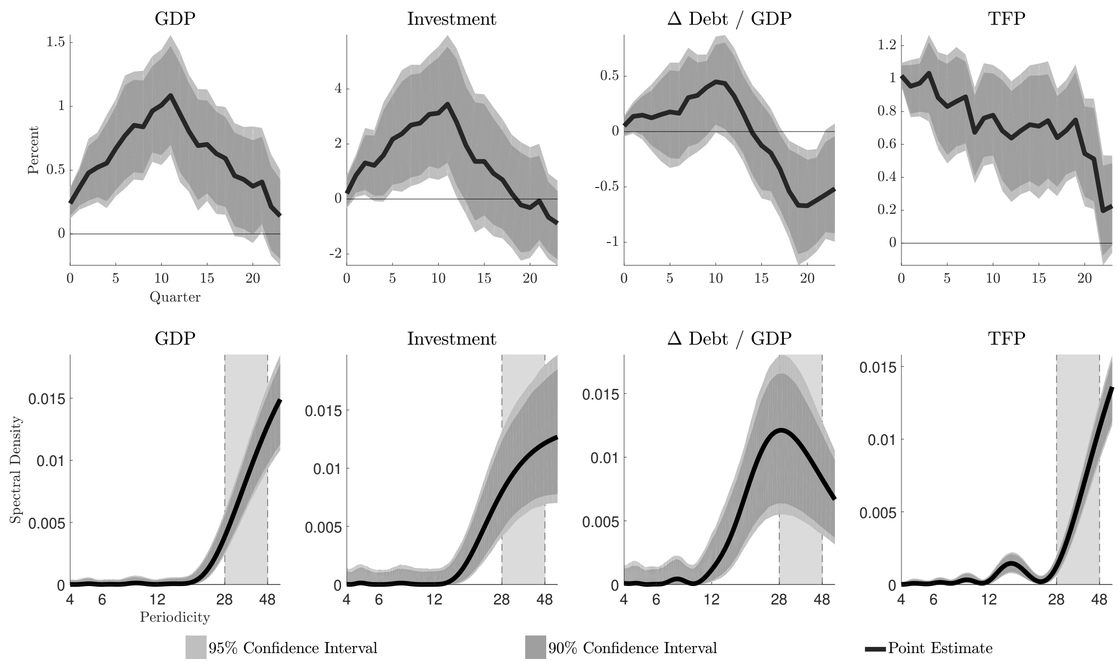


Figure 2.3: Impulse responses and spectral densities of a TFP shock.

Note: Technology shocks are the innovation of detrended TFP after regressing it on its own lags, lags of the first principal component of a large dataset of aggregate economic variables and news shocks estimated as in Barsky and Sims (2011). Impulse responses (top panel) are estimated using local projections method. Confidence intervals are computed using the block-bootstrap method described in Kilian and Kim (2011). Conditional spectral densities (bottom panel) are computed from the Fourier transform of the estimated MA.

The top panel of Figure 2.3 shows the impulse responses of real GDP, investment and the change in nonfinancial corporate debt as a fraction of GDP, to a positive transitory technology shock. An unanticipated improvement of TFP leads to a hump-shaped response of real GDP and investment, aggregate debt rises during the initial build-up and decreases while the economy returns to its long run trend. To verify whether these impulse responses can account for the spectral properties of the data, we compute the spectral densities implied by the estimated coefficients of the moving averages. The bottom panel of Figure 2.3 shows that the spectral densities of real GDP and investment conditional to a TFP shock are monotonically increasing over business cycle periodicities. This poses a challenge to TFP-based explanations of boom-bust cycles.

Conditional test for the presence of a local peak The lack of a local peak in the spectral density of output, investment, and TFP observed in Figure 2.3 suggests that technology shocks cannot account for spectral properties of the data shown in Figure 2.1. To make the point, we construct a test for the presence of a significant local peak in the spectral density conditional to a structural shock. The test procedure echoes Canova (1996) and Reiter and Woitek (1999) who design a test for the presence of a peak for the unconditional spectral density. Details of our procedure are presented in the Appendix B.7. The idea is to test if the shape of the conditional spectral density around a particular frequency range is not statistically different from the spectral density implied by an autoregressive process of order one. More specifically, define D_1 the average estimated spectral density over a range around 34 quarters, and D_2 the average estimated spectral density over a range around 45 quarters. The test statistic is the ratio $D \equiv D_1/D_2$. A value of D bigger than one indicates the spectral density is decreasing in the range 34 to 45 quarters. The spectral density associated to an AR(1) process, in contrast, is monotonically increasing in the periodicity. Therefore we test the null hypothesis $H_0 : D = D^*$ where D^* is the value implied by an AR(1) with persistent parameter estimated from the data, against the alternative $H_1 : D > D^*$. Results for the technology-implied spectral density are reported in Table B.1. We fail to reject the null hypothesis of absence of a local peak for GDP, investment, and TFP.

Taken together our reduced form and conditional evidence points at the presence of oscillatory properties of the data that do not appear to be captured by movements in TFP. In the next section we build a model that helps us rationalizing the findings and propose “pure" sentiment shock - defined as shifts in expectations unrelated to fundamental - as a natural candidate to explain the spectral properties of the data. In section 2.4 we construct novel empirical evidence in favor of this hypothesis and show that the model can reproduce the responses to sentiment and technology shocks together with the unconditional spectral densities of the data.

2.3 A model of conditional cycles

In this section we show that a standard Real Business Cycle model augmented with financial frictions can rationalize the cyclicality conundrum. Azariadis et al. (2015) document that unsecured firm credit is procyclical whereas collateralized debt is acyclical. Building on their findings, we assume a type of solvency constraint that allows firms to borrow up to a fraction of their market value. Furthermore, we introduce short and long term debt as in Jermann and Quadrini (2012). This form of financial friction combined with procyclical fluctuations of long-term debt generate strong internal amplification and cyclical dynamics in response to serially uncorrelated shifts in expectations. For plausible parametrizations of the financial constraint, we find that the model displays dynamic multiplicity of equilibria due to self-fulfilling changes in expectations (a.k.a sunspots). In this environment, waves of optimism unrelated to present and future fundamentals, generate temporary expansions followed by recessions.

Importantly, our model stands in stark contrast to the class of models of self-fulfilling business cycle due to aggregate increasing returns to scale as described in Benhabib and Farmer (1994).[8] Amplification in the form of increasing returns would strongly influence the transmission of technology shocks, thus, while these models can generate endogenous oscillatory dynamics, they cannot *simultaneously* account for the empirical evidence on technology shocks.

For expositional reasons, we present first a benchmark model featuring intertemporal debt as the only state variable. In the next section we identify sentiment shocks in the data and augment the model with capital and external consumption habit to match empirical responses. We further validate model's performance by showing that it does a good job in matching the spectral properties of the data.

2.3.1 Firm sector

There is a continuum $i \in [0,1]$ of firms with a gross revenue function $F(z_t, k_t, n_t) = z_t k_t^{\theta} n_t^{1-\theta}$. The variable z_t is the stochastic level of productivity common to all firms, n_t is the labor input, k_t is the capital input which we assume to be constant and equal to one for now. Firms issue noncontingent bonds b_{t+1} at a price b_{t+1}/R_t. We assume that firms receive a tax advantage such that given the interest rate r_t, the effective gross interest rate for the firm is $R_t = 1 + r_t(1-\tau)$ where τ is the tax benefit. Thus, firms are effectively more impatient than households so that if financial markets are not too tight the equilibrium stock of debt will be positive. In

[8] Examples in this class are Farmer and Guo (1994), Wen (1998), and Liu and Wang (2014).

addition to the intertemporal debt, firms raise funds with an intraperiod loan, ℓ_t, to finance working capital. Because revenues are realized at the end of the period, working capital is required to cover the intraperiod cash flow mismatch. The loan ℓ_t is paid at the end of the period with no interest.[9]

The timing of the events is the same as in Jermann and Quadrini (2012). Shocks realize at the beginning of the period. Firms enter the period with outstanding debt equal to b_t and choose labor n_t, the new intertemporal debt b_{t+1} and distribute dividends d_t. Since payments are made before producing, the intraperiod loan is

$$\ell_t = w_t n_t + \phi(d_t) + b_t - b_{t+1}/R_t,$$

where $\phi(d_t) = d_t + \kappa(d_t - \bar{d})^2$ includes a convex distribution cost of dividends which captures documented evidence of preferences for dividend smoothing (Lintner, 1956). The end of period firm's budget constraint is

$$b_{t+1}/R_t + F(z_t, n_t) = w_t n_t + \phi(d_t) + b_t. \tag{2.1}$$

It follows that firm's revenues are equal to the intraperiod loan, that is $\ell_t = F(z_t, n_t)$.

Incentive constraint. When production is complete, firms decide whether or not repay the intraperiod loan they owe to the household. Consistent with recent evidence on the procyclicality of unsecured debt (see Azariadis et al., 2015), we as-

[9] The assumption of two types of debt is made for analytical convenience. In particular the intratemporal debt can be replaced with cash that firms carry from the previous period. Cash would then be used to finance working capital and pay part of dividends.

sume that contract enforcement is imperfect so that firms have incentives to default. If a firm defaults it can divert its end of period revenues $y_t \equiv F(z_t, n_t)$. However, a defaulting firm can be caught with probability γ, in which case its assets will be liquidated and the firms will cease to operate. If a firm is not caught, it continues to retain access to credit in future periods.[10]

Formally, a firm defaults if

$$y_t + (1-\gamma)E_t m_{t,t+1} V_{t+1} > E_t m_{t,t+1} V_{t+1},$$

where $m_{t,t+1}$ is the households' stochastic discount factor, and V_{t+1} is the firm's future value defined as the net present value of future dividends.

Because shocks realize at the beginning of period, there is no intraperiod uncertainty. Thus we can write the following incentive constraint that deters default in equilibrium,

$$\gamma E_t m_{t,t+1} V_{t+1} \geq y_t. \tag{2.2}$$

The left hand side of the constraint is equal to γ times firms' market value and decreases with the amount of intertemporal debt $b_{t,t+1}$. Whereas the right hand side is equal to the end-of-period revenues y_t which are equal to firms' intra-period loan. Hence, the incentive constraint in eq. (2.2) is effectively limiting both types of firms' debt. Importantly, in deciding between short and long-term debt, firms understand that an increase in b_{t+1} tightens their borrowing constraint as it limits

[10] Assuming that in the case of being caught a firm would also loose its revenues does not quantitatively alter our results.

their future ability to distribute dividends, but they do not internalize the effects that a change in production have on their market value through movements in the discount factor $m_{t,t+1}$. This type of externality will turn out to be crucial to generate both amplification and boom-bust phenomena.

The problem of the individual firm can be written recursively as

$$V_t = \max_{d_t, n_t, b_{t+1}} \left\{ d_t + E_t \left[m_{t,t+1} V_{t+1} \right] \right\} \tag{2.3}$$

subject to (2.1) and (2.2).

Firm's first order conditions are

$$(1 + \mu_t \gamma) R_t E_t \left[m_{t,t+1} \frac{\phi'(d_t)}{\phi'(d_{t+1})} \right] = 1 \tag{2.4}$$

$$\frac{w_t}{1 - \mu_t \phi'(d_t)} = (1 - \theta) \frac{y_t}{n_t} \tag{2.5}$$

where μ_t is the Lagrange multiplier associated to the incentive constraint. Equation (2.4) is the first order condition of new intertemporal debt b_{t+1}, and captures the fact that the marginal cost of debt increases with $\mu_t$and with the effective firm's discount factor defined as the household's discount factor, $m_{t,t+1}$ times the expected decrease in the cost of dividends. The first order condition of labor input (2.5) shows that financial frictions introduce a time varying labor wedge. When debt limits are looser the labor wedge declines, that is μ_t decreases, so that firms borrow more intra-period and the labor demand increases.

Furthermore, looser credit constraints also increase the intertemporal loan. To see this, combine the budget constraint of the firms with the optimality condition for labor:

$$\frac{b_{t+1}/R_t - b_t}{y_t} = \frac{\phi(d_t)}{y_t} - (1-\theta)\mu_t\phi'(d_t) - \theta.$$

As credit market relaxes, that is μ_t decreases, for a given dividend to output ratio, the intertemporal debt rises.

2.3.2 Households sector and general equilibrium

There is a continuum of homogeneous utility-maximizer households. Households are the owners of firms. They hold equity shares and noncontingent bonds issued by firms. Households' instantaneous utility function is

$$U(c_t, n_t) = \frac{c_t^{1-\omega} - 1}{1-\omega} + \alpha \log(1 - n_t).$$

The household's budget constraint is

$$c_t + s_{t+1}p_t + \frac{b_{t+1}}{1+r_t} = w_t n_t + b_t + s_t(d_t + p_t) - T_t \tag{2.6}$$

where s_t is the equity shares and p_t is the market price of shares. The government finances the tax benefits to firms through lump-sum taxes equal to $T_t = B_{t+1}/[1 + r_t(1-\tau)] - B_{t+1}/(1 + r_t)$. The first order conditions with respect to n_t,b_{t+1}, and s_t

are

$$w_t = -\frac{U_n(c_t, n_t)}{U_c(c_t, n_t)} \tag{2.7}$$

$$U_c(c_t, n_t) = \beta(1 + r_t)E_t U_c(c_{t+1}, n_{t+1}) \tag{2.8}$$

$$p_t = \beta E_t \left\{ \frac{U_c(c_{t+1}, n_{t+1})}{U_c(c_t, n_t)}(d_{t+1} + p_{t+1}) \right\} \tag{2.9}$$

Given the aggregate states **s**, that are productivity z and aggregate bonds B we can define the general equilibrium as follows:

Definition: *A recursive competitive equilibrium is defined as a set of functions for (i) households' policies $c^h(\boldsymbol{s}, b)$, $n^h(\boldsymbol{s}, b)$ and $b^h(\boldsymbol{s}, b)$; (ii) firms' policies $d(\boldsymbol{s}, b)$, $n(\boldsymbol{s}, b)$, and $b(\boldsymbol{s}, b)$; (iii) firms' value $V(\boldsymbol{s}, b)$; (iv) aggregate prices $w(\boldsymbol{s})$, $r(\boldsymbol{s})$, and $m(\boldsymbol{s}', \boldsymbol{s})$; (v) law of motion for the aggregate states $\boldsymbol{s}' = \psi(\boldsymbol{s})$. Such that: (i) household's policies satisfy conditions (2.7) and (2.8); (ii) firm's policies are optimal and $V(\boldsymbol{s}, b)$ satisfies the Bellman's equation (2.3); (iii) the wage and the interest rate clear the labor and bond markets; (iv) the law of motion $\psi(\boldsymbol{s})$ is consistent with individual decisions and stochastic processes for productivity.*

2.3.3 Inspecting the mechanism

The key externality in the model is that firms do not fully internalize the effects of their production decisions on their market value. In particular, while they understand that a higher level of debt reduces their market value because it limits the ability to distribute future dividends, they do not internalize the feedback loop between output and their market value. Absent of adjustment cost of dividends, *i.e.* $\kappa = 0$, credit market amplification depends upon the elasticity of firms' production to the households' stochastic discount factor. This elasticity is equal to

$$\frac{\partial log(y_t)}{\partial log(m_{t,t+1})} = \frac{\beta\tau}{\gamma(1-\mu)(1-\tau+\tau\beta)^2}\left[\frac{(1-n)(1-\theta)}{(\omega-1)(1-n)(1-\theta)+1}\right] \equiv \xi,$$

where $\mu = \tau(1-\beta)/\gamma(1-\tau+\tau\beta)$.

If credit market frictions are severe, that is the probability of being excluded from financial market γ is low or the tax advantage on debt τ is high, firms are more responsive to changes in their continuation value reflected by changes in the stochastic discount factor. Sufficiently high values of ξ give rise to self-fulfilling equilibria. Suppose lenders and borrowers are optimistic regarding firms' market value, this relaxes the financial constraint and implies an increase in the credit supply. As a consequence, production and households' labor income increase which raise firms' market value through an increase in the stochastic discount factor $m_{t,t+1}$ validating the initial shift in expectations.

Formally, take a first order approximation around the steady state, aggregate output can be expressed as

$$\hat{y}_t = \frac{\omega\xi}{\omega\xi-1}E_t\hat{y}_{t+1} - \frac{1}{\zeta(\omega\xi-1)}\hat{z}_t \tag{2.10}$$

where $\zeta \equiv (\omega-1)(1-n)(1-\theta)+1$.

When $\omega\xi > 1/2$, current aggregate output is a convex function of future output which is sufficient to generate indeterminacy.

Note that the impact of technology shocks on aggregate output is ambiguous. By increasing end of period revenues, a positive technology shock raises firm's incentives to divert funds thereby increasing the right-end-side of the incentive constraint in eq. (2.2). Whether firm's market value increases more than firm's revenue depends upon firm's willingness to distribute dividends. We find that for plausible parametrizations, the Lagrange multiplier μ_t *increases* in response to a positive technology shock.

Thus financial constraints amplify shifts in expectations while they dampen the response to technology shocks. Yet, why do boom-bust episodes occur? Theorem 1 below lists the necessary conditions under which boom-bust fluctuations may obtain in response to perturbations from the economy's steady state.

Theorem 1 *Boom-bust phenomena obtain only if*

i. The equilibrium is indeterminate.

ii. Adjustment costs are non zero, that is $\kappa > 0$.

Proof is relegated in Appendix B.8.

Condition $i.$ states that if the credit market amplification channel is strong enough, so that indeterminacy obtains, then the economy can also be subject to oscillatory dynamics.[11] The intuition is that after an initial expansion, firms have accumulated

[11] This property is not specific to the environment described here. Gu et al. (2013) discuss the link between indeterminacy and cycles in the context of financial frictions of different forms.

large amount of debt which limits their ability to borrow and produce. As firms decrease production they do not internalize the adverse effects on their market value. The stronger are the effects of this externality the larger is the drop in current production. The reason why adjustment cost of dividends is necessary to obtain cycles is more subtle. Besides the static amplification mechanism described above, the model displays dynamic substitutability between current and future production generated by movements in firms' net worth. An increase in new debt brings about higher current production but it decreases future firms' net worth which negatively affects the subsequent level of production. Absent dividend adjustment costs, firms with a high level of outstanding debt would finance production by decreasing the amount of distributed dividends, therefore limiting the impact that changes of net worth on their production decisions, thus preventing the large accumulation of debt after the expansion to generate a recession.

2.3.4 Parametrization and theoretical impulse responses

The sunspot shock is defined as an i.i.d. expectation error of firm's value that is not correlated with fundamentals

$$\widehat{V}_t - E_{t-1}\widehat{V}_t = u_t$$

where $u_t = \epsilon_{s,t} + \psi_z \epsilon_{z,t}$.

The terms $\varepsilon_{s,t}$ and $\epsilon_{z,t}$ are respectively the sunspot shock and the technology shock.[12] The natural logarithm of technology is assumed to follow an AR(1) process as

$$\widehat{z}_t = \rho_{z,t}\widehat{z}_{t-1} + \epsilon_{z,t}.$$

We calibrate the model to a quarterly frequency consistent with the frequency of the data. We set β in order to match a 3% annual interest yield on bonds. Following Jermann and Quadrini (2012) tax shield τ and capital's share of income θ are set equal to 0.35 and 0.36, respectively. With the aim of emphasizing the difference between the two shocks, we set the inverse of households' intertemporal elasticity of substitution ω to 1.2, the probability of being caught in case of default γ to 0.1 and the degree of adjustment cost to dividends κ to 2.3. The parameter ρ_z governs the persistence of the technology process and is set equal to 0.93 consistent with the law of motion of detrended TFP estimated in the data. We assume the expectation error u_t and the technology shock to be uncorrelated, so that ψ_z is equal to zero.[13]

Figure 2.4 shows the theoretical impulse responses of the model to a sunspot shock and to a technology shock. In response to the sunspot shock the economy experiences an initial boom characterized by an increase output, consumption and hours. The associated increase in debt has two effects. On the one hand, it reflects

[12] Note that inserting the sunspot on output would not alter our results. It is easy to show that

$$\widehat{V}_t - E_{t-1}\widehat{V}_t = \omega(\widehat{y}_t - E_{t-1}\widehat{y}_t).$$

[13] Note that ψ_z equal zero implies a zero-impact response of output and firm's value after a technology shock. While this is an implausible restriction that will be relaxed in the quantitative exercise, it allows to generate a starker difference between the dynamics induced by the two shocks.

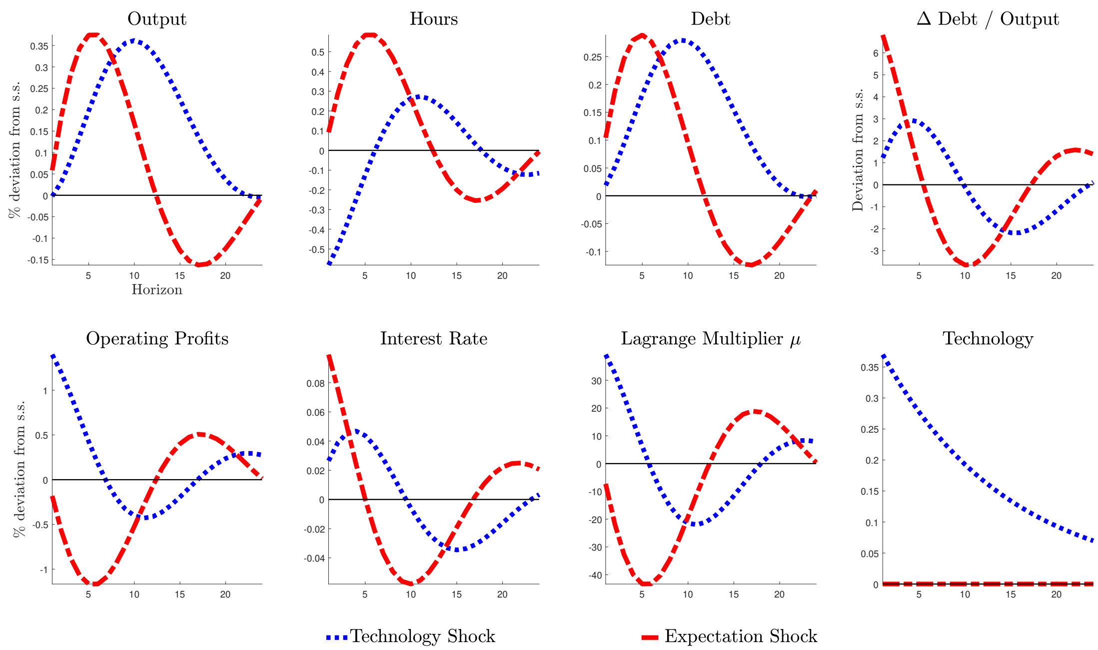


Figure 2.4: Model impulse responses to a technology shock and to sunspot shock

an increase in households' savings which increases the supply of credit generating a decrease in the real rate and an increase in firms' market value. On the other hand, larger outstanding debt hinders firms' ability to pay current and future dividends which deteriorates their market value. Which of these two forces prevails depends upon the level of firms' profitability. As production increases firms' profitability falls so that firms' market value decreases, the financial constraint tightens and output starts declining. During the contraction phase, households are less willing to lend which results in an increase in the real rate, a decrease in firm's value and a further tightening of the financial market. This negative vicious circle reinforces as households' savings decline, ultimately bringing about a recession. Importantly, even though agents know about the incoming recession their actions magnifies the decline in output.

A positive technology shock generates hump-shaped dynamics in all the main macroeconomic variables. By increasing incentives to divert funds, a positive technology shock tightens the financial constraint which dampens the impact response of output. Importantly, the response of debt and output is comparable to the ones after a sunspot shock, suggesting that looking at measures of firms' indebtedness such as the debt to GDP ratio may not be the best predictor of a crisis.

Importantly, expectation-driven fluctuations arise also in an economy where fundamentals, that is technology, preferences, or government policies, do not change and this is common knowledge. This distinguishes them from noise shocks arising from *ex post* erroneous beliefs on future changes of technology. Bearing this distinction in mind, in the next section, we estimate expectation shocks unrelated to fundamentals and to rational expectations of fundamentals. We find that these shocks generate boom-bust dynamics consistent with the quantitative prediction of an extended version of the model.

2.4 Identifying sunspot shocks using survey data

In this section we estimate the sunspot shock as a “pure" sentiment shock, that is a shock that reflects a change in expectations disconnected from changes in expectations on future TFP and realizations of TFP. To this end, we use quarterly one-year-ahead expectations on a number of key macroeconomic variables formed by both professional forecasters and households. We proceed in three steps.

The Survey of Professional Forecasters and the Survey of Consumer Expectations include expectation data on a number of variables, such as future real GDP growth, investment, and consumption. Our theory does not point at a particular variable, rather expectation shocks should be reflected into a change of expectations common across all variables in the surveys that capture information upon expected future business conditions. Therefore, as a first step, we construct an expectation indicator $\hat{S}_t$ from the first principal component of all the relevant available expectation data. The sample includes seven quarterly variables from 1982:Q2 to 2018:Q4.

Second, we regress the indicator $\hat{S}_t$ on a battery of controls in order to capture variations in expectations that are “extrinsic", that is, exogenous to fundamentals and to changes in expectations on future fundamentals. Formally, let the process of detrendend TFP be represented by the following news representation

$$\log(TFP)_t = A(L)\log(TFP)_{t-1} + \varepsilon_t^z + \sum_{k=1}^{\infty} \varepsilon_{t-k}^k$$

where ε_{t-k}^k is a news shock on TFP k-period ahead which is part of time t agents' information set, and ε_t^z is the surprise shock of technology. Let S_t^K be the indicator that summarizes revision of agents expectations on the economic activity K-period ahead. We assume that these revisions depend upon current technology shocks, expectations on future technology, and expectation shocks. Specifically,

$$S_t^K = \lambda_0 \log TFP_t + \sum_{k=1}^{K} \alpha_k \varepsilon_t^k + \varepsilon_t^s$$

where expectations on future technology are a linear combination of news upon technology up to K horizons. Hence, in order to identify *extrinsic* expectation shocks one needs to cleanse changes in expectations, proxied by $\hat{S}_t$, from the realized level of TFP and expectations about future TFP up to the horizon K. In other words, we want the estimated expectation shock to satisfy two conditions: (i) the estimated shock must be uncorrelated with future TFP realizations; (ii) the shock has to be uncorrelated with noise shocks, defined as ex-post wrong beliefs on future TFP. [14]

We proxy expectations on future TFP with TFP news shocks identified as in Barsky and Sims (2011). However, this controlling set may no be large enough to satisfy the two conditions above. To overcome this issue we add two additional set of controls. First, we control for future realizations of TFP so as to guarantee that the estimated shock has no impact on future TFP. Second, as shown by Chahrour and Jurado (2018), one can recover noise shocks by adding future news and realizations of TFP to the econometrician's information set. Thus, we further control for future realizations of the identified news shock. Specifically, expectation shocks are estimated from the following equation:

$$\hat{\varepsilon}^s_t = \hat{S}_t - \sum_{k=0}^{\bar{k}} \widehat{\lambda}_k TFP_{t+k} - \sum_{k=0}^{\bar{k}} \widehat{\alpha}_k \varepsilon^{BS}_t - \mathbf{X}_t \widehat{\beta}$$

where ε^{BS}_t is the news shock estimated using the procedure in Barsky and Sims (2011), and $\mathbf{X}_t$ is a vector of additional control variables, including past realizations of TFP and news, other shocks to fundamentals such as monetary policy and fiscal

[14] As shown by Beaudry and Portier (2004) noise shocks in the form of ex-post wrong beliefs on future TFP can give rise to Pigouvian cycles and therefore are a competing candidate to the explanation of the reduced form evidence presented in Section **??**. However, we find that controlling for this particular type of beliefs has small quantitative changes on the variance explained by the expectation shock, suggesting that noise shocks play only a minor role in shaping expectations.

shocks, and past values of the first two principal components from a large data set of U.S. aggregate variables. Interestingly, even after controlling for virtually all available sources of fundamental fluctuations, estimated expectation shocks explain approximately half of the changes in the expectation indicator $\hat{S}_t$.

In the last step, we estimate the impulse response to an expectation shock using Local Projections as in Jordà (2005). Specifically, for each variable of interest Y, we run the following series of regressions

$$Y_{t+h} = \theta^h \hat{\varepsilon}^s_t + \sum_{j=1}^{J} \left[\delta_j \hat{\varepsilon}^s_{t-j} + \lambda_j Y_{t-j} + \mathbf{PC}_{t-j} \Gamma_j \right] + \nu_{t+h} \text{ for } h = 0, 1, \ldots, H \quad (2.11)$$

where θ^h is the response of Y to an expectation shock after h periods, and PC is a vector including the first two principal component from a set of U.S. aggregate variables. We use four lags, that is $J = 4$, in the baseline specification.

Figure 2.5 shows the responses of real GDP, real investment, and the change of non-financial corporate debt divided by real GDP to a one standard deviation expectation shock. Real GDP, investment and debt flow exhibit significant oscillatory dynamics. In particular, after a positive expectation shock, the economy enters an expansion followed by a recession after about two years. Importantly, the conditional spectral densities exhibit a peak associated to periodicities of 8 to 10 years, in line with the reduced form evidence presented earlier. Table B.1 in Appendix B.7 reports the p-values for the test of a local peak in the spectral density implied by expectation shocks. The null hypothesis of absence of a local peak is rejected for all variables, with the exception of TFP.

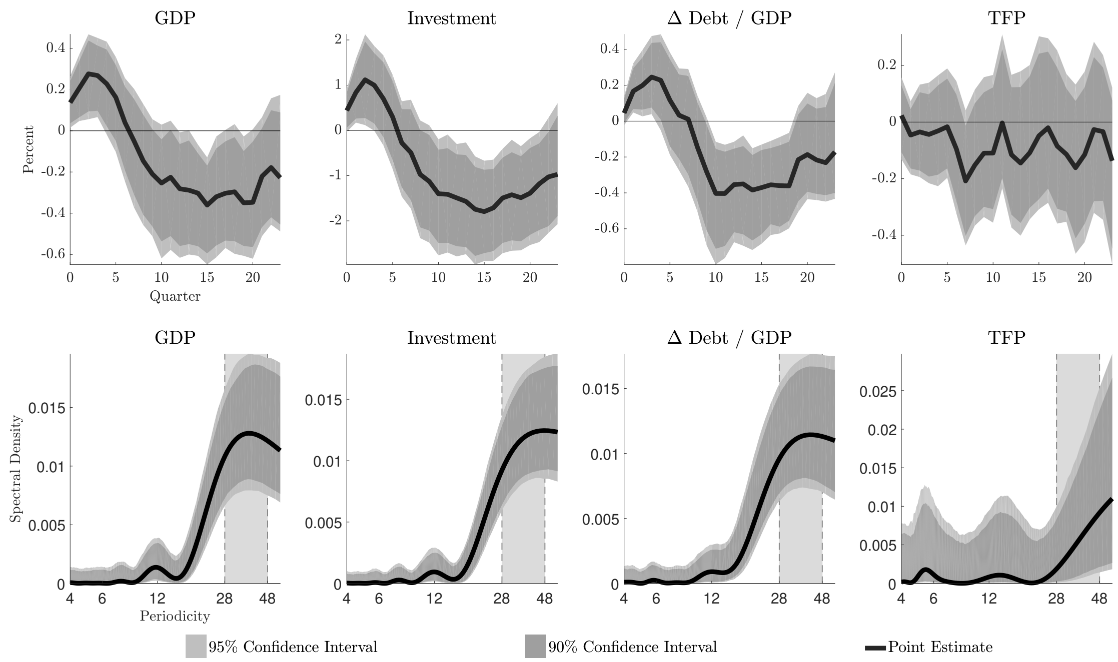


Figure 2.5: Impulse responses and conditional spectral densities to an expectation shock

Note: Expectation shocks are estimated as the innovations in S_t orthogonal to present, past, and future realization of TFP and expectations on TFP. Impulse responses (top panel) are estimated using local projections method. Confidence intervals are computed using the block-bootstrap method described in Kilian and Kim (2011). Conditional spectral densities (bottom panel) are computed from the Fourier transform of the estimated MA.

2.4.1 Robustness checks

In this section we show that the results in Figure 2.5 are robust to different detrending techniques, additional controls, and the expectation variables used to construct the indicator S_t. Given that our endogenous variables are non-stationary, in the baseline specification we detrend the variables using a Band-Pass filter which excludes periodicities above 100 quarters. In order to argue that the oscillatory dynamics implied by an expectation shock is not specific to the detrending technique, in Figure 2.6 we show robustness checks where endogenous variables are detrended using (i) first differences (and the cumulated), (ii) linear time trend, (iii) quadratic time trend, and (iv) Hodrick-Prescott filter. Results are in line with the baseline specification and most of the estimates lie between the confidence intervals of the main specification.

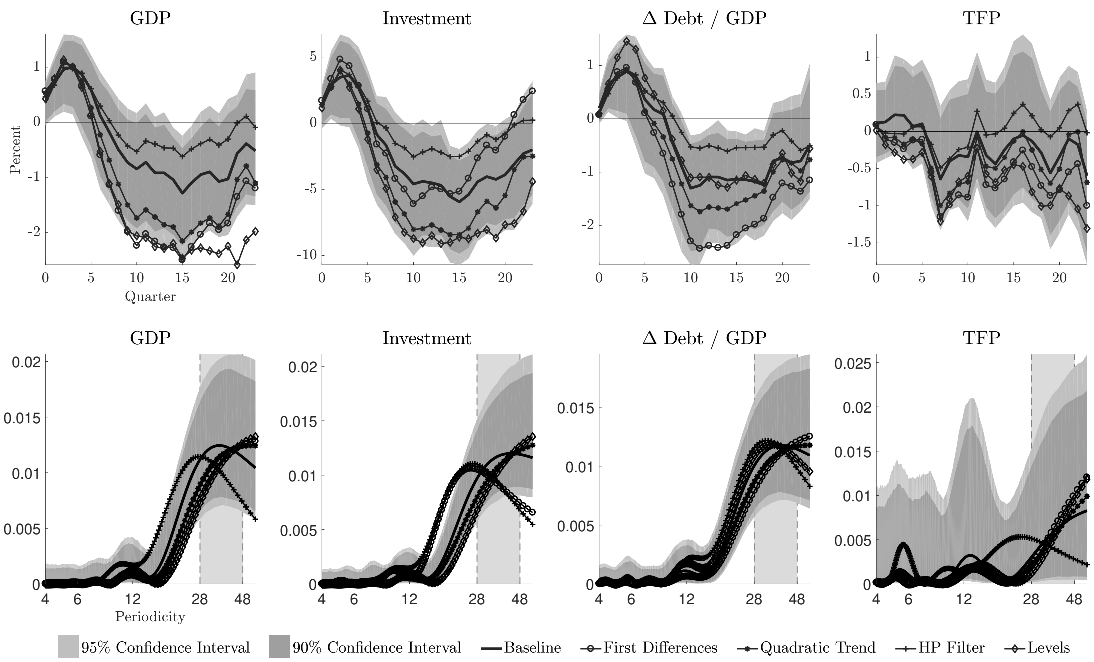


Figure 2.6: Impulse responses and conditional spectral densities to an expectation shock

Note: Point estimates (continuous line) are from the baseline specification presented in Figure 2.5. The figure shows the robustness of the point estimate to various detrending techniques.

Figure 2.7 reports results for four additional variations of the baseline specification. First, we increase the number of lags and the number of principal components in the regression equation of the expectation shock. Second, we control for the present and the past of other shocks to fundamentals such as oil shocks, fiscal shocks, military spending news shocks and monetary policy shocks. Third, we check whether results are sensitive to the choice of the indicator for the revisions of expectations.

Specifically, we use only revisions on one-year-ahead output growth from the SPF and find results that are not significantly different from the baseline. Finally, we check that results are robust to the number of lags and principal components used in the LP.

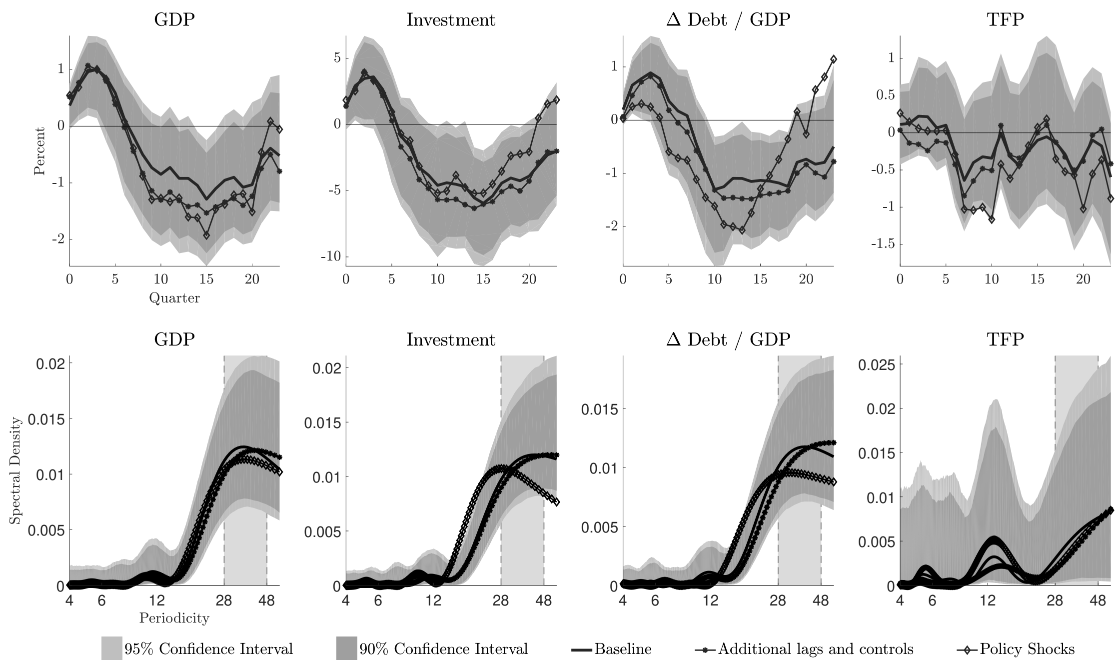


Figure 2.7: Impulse responses and conditional spectral densities to an expectation shock

Note: Point estimates (continuous line) are from the baseline specification presented in Figure 2.5. The figure shows the robustness of the point estimate to various controls (see text).

2.5 Model with capital and external consumption habit

In this section we augment the model with variable capital, investment-adjustment costs and external consumption habit. The equilibrium equations of the extended model are:

$$w_t U_c(c_t, c_{t-1}, n_t) = -U_n(c_t, c_{t-1}, n_t) \tag{2.12}$$

$$E_t[m_{t,t+1}(R_t - \tau)] = 1 - \tau \tag{2.13}$$

$$w_t n_t + b_t - \frac{b_{t+1}}{R_t} + d_t = c_t \tag{2.14}$$

$$\big[1 - \mu_t \phi'(d_t)\big] F_n(z_t, k_t, n_t) = w_t \tag{2.15}$$

$$k_{t+1} = (1-\delta)k_t + \left[\frac{\varsigma_1}{1-\nu}\left(\frac{i_t}{k_t}\right)^{1-\nu} + \varsigma_2\right] k_t \tag{2.16}$$

$$\begin{aligned} E_t\Bigg\{ m_{t,t+1}\frac{\phi'(d_t)}{\phi'(d_{t+1})}(1+\mu_t\gamma)\Bigg\{ \big(1 - \phi'(d_{t+1})\mu_{t+1}\big) F_k(z_{t+1}, k_{t+1}, n_{t+1}) + \\ + \frac{1}{\varsigma_1}\left(\frac{i_{t+1}}{k_{t+1}}\right)^{\nu}\left[1 - \delta + \frac{\varsigma_1 \nu}{1-\nu}\left(\frac{i_{t+1}}{k_{t+1}}\right)^{1-\nu} + \varsigma_2\right]\Bigg\}\Bigg\} = \frac{1}{\varsigma_1}\left(\frac{i_t}{k_{t-1}}\right)^{\nu} + E_t\big[m_{t,t+1}\phi'(d_t)\mu_t\gamma\big] \end{aligned} \tag{2.17}$$

$$(1+\mu_t\gamma)E_t\left[m_{t,t+1}\frac{\phi'(d_t)}{\phi'(d_{t+1})}R_t\right] = 1 \tag{2.18}$$

$$y_t - w_t n_t - b_t + \frac{b_{t+1}}{R_t} - i_t = \phi_t(d_t) \tag{2.19}$$

$$\gamma E_t\big[m_{t,t+1}V_{t+1}\big] = y_t \tag{2.20}$$

where $y_t = F(z_t, k_t, n_t) = z_t k_t^{\theta} n_t^{1-\theta}$ and $\phi(d_t) = d_t + \kappa(d_t - \bar{d})^2$. Moreover, the stochastic discount factor is $m_{t,t+1} \equiv \beta(U_{c,t+1}/U_{c,t})$ and value of the firm is defined as $V_t = d_t + E_t\big[m_{t,t+1}V_{t+1}\big]$. Finally, $U_c(c_t, c_{t-1}, n_t) = (c_t - \iota c_{t-1})^{-\omega}$ and $U_n(c_t, c_{t-1}, n_t) = -\alpha(1-n_t)^{-\omega_2}$.

2.5.1 Calibration and impulse response matching

Following Christiano et al. (2005) we divide the model parameters in two different groups. The first group is calibrated using unconditional moments or results from previous studies while the remaining parameters are estimated via impulse response matching. In both cases, the model is calibrate at a quarterly frequency. In the first group, the discount factor β, the capital share of income θ, and tax shield τ have the same values presented in section 2.3. The multiplicative parameter which governs the utility of leisure α is chosen such that the steady state value of n is equal to 0.3. Parameters ς_1 and ς_2 (capital-adjustment costs) are set such that in the steady state the depreciation rate is equal to $\delta = 0.025$ and the steady state Tobin's q is equal to one. Parameter ψ_z, which captures the correlation between technology shocks and the forecast error on firms' value, is set in order to match the impact of a 1% technology shock on real GDP. Moreover, the parameter γ, which governs the tightness of the incentive constraint, is set in order to match an empirical average debt-to-output ratio of 3.36. Finally, κ is calibrated in order to have a model standard deviation of equity payout over output equal to the empirical standard deviation.

The second group includes the vector of parameters $\Sigma = (\rho_z, \omega, \iota, \nu)$: the persistence of technology process, ρ_z; the inverse of households' intertemporal elasticity of substitution, ω; the external consumption habit parameter, ι; the degree of capital adjustment cost, ν. We choose Σ in order to minimizes the following object

$$J = \min_{\Sigma}[\hat{\Psi} - \Psi(\Sigma)]' V^{-1} [\hat{\Psi} - \Psi(\Sigma)]$$

where $\hat{\Psi}$ denotes the empirical impulse responses of GDP, Consumption, hours worked and TFP to both technology and expectation shocks, and $\Psi(\Sigma)$ is the model-implied counterpart of $\hat{\Psi}$. Finally, V is a diagonal matrix which gives different weights to the target estimates. Table 2.1 reports the parameter values of the model.

Parameter	**Interpretation**	**Value**	**Target**
α	Disutility of labor	8.785	Hours in steady state $= 0.3$
β	Discount factor	0.99	Annual bond yield $= 3\%$
τ	Tax shield	0.35	Jermann and Quadrini (2012)
θ	Capital share	0.36	Standard
δ	Capital depreciation	0.025	Standard
ς_1	Capital adj. cost (1)	δ^{ν}	Depreciation rate $= \delta$
ς_2	Capital adj. cost (2)	$\delta - \delta/(1-\nu)$	Tobin's $q = 1$
ψ_z	Corr tech and exp error	0.24	Impact of tech. shock on GDP
γ	IC parameter	0.12	$b/Y = 3.36$
κ	Dividend cost	3.01	$std(d/Y) = 0.024$
ρ_z	Technology persistence	0.93	IRF matching estimation
ω	CRRA consumption	1.25	
ι	Consumption habit	0.45	
ν	Capital adj. cost	0.55	

Table 2.1: Model's parameter values.

2.5.2 Model performance

Figures 2.8 and 2.9 plot the theoretical impulse response of the model against their empirical counterparts. The model does a good job in reproducing the empirical impulses to both shocks. In particular, we estimate the model consistent measure of labor wedge and find that the responses are in line with the predictions of the model.

Figure 2.10 shows the empirical conditional spectral densities against their model counterpart. The theoretical spectral densities implied by the model are within the range of the confidence bands of the empirical ones.

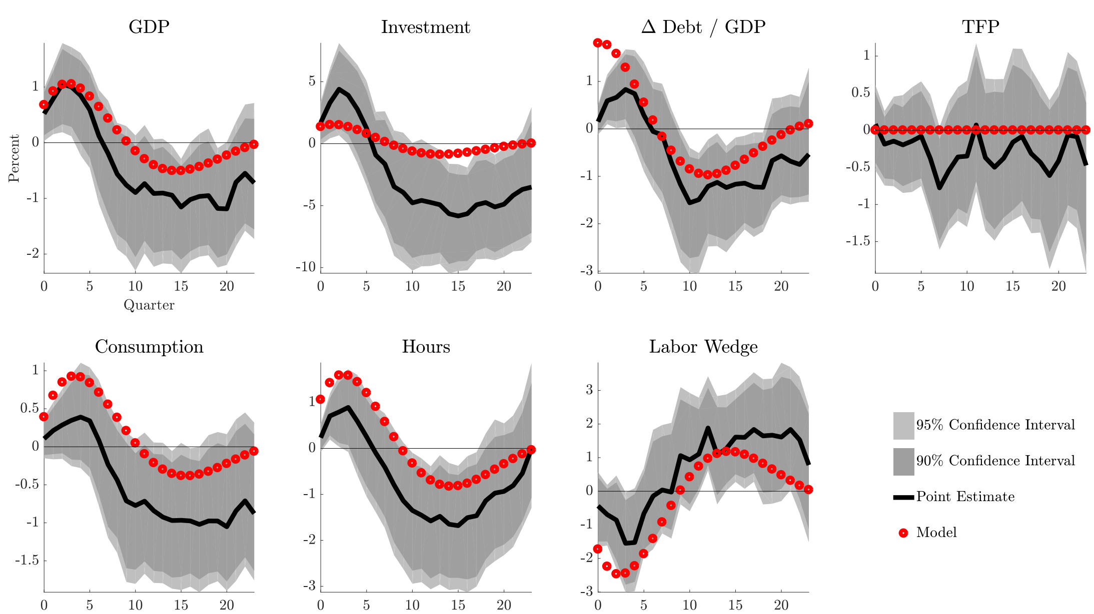


Figure 2.8: Model vs empirical IRFs to an expectation shock

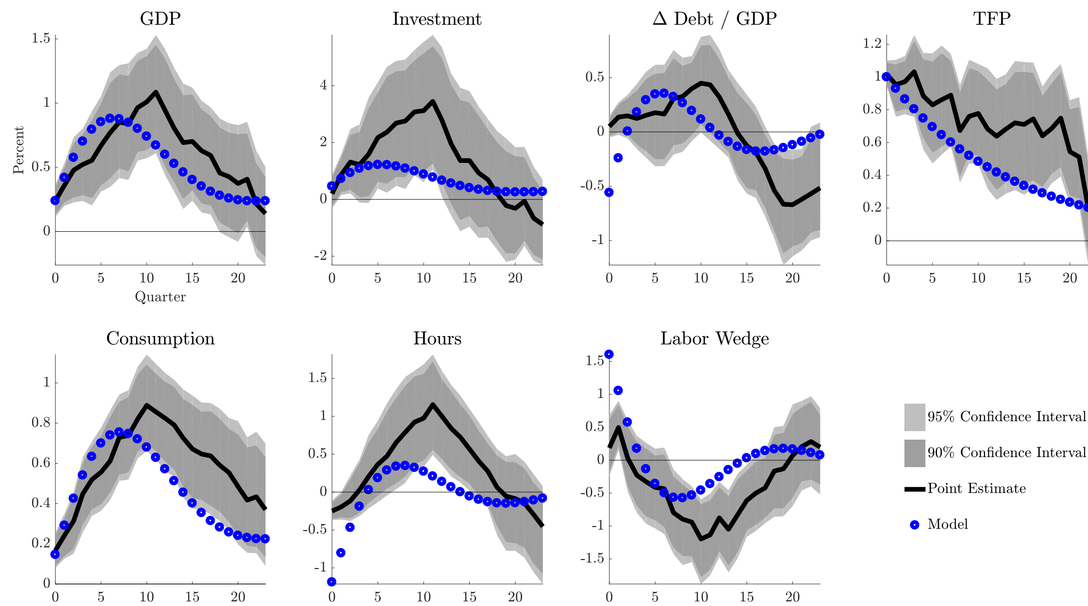


Figure 2.9: Model vs empirical IRFs to a technology shock

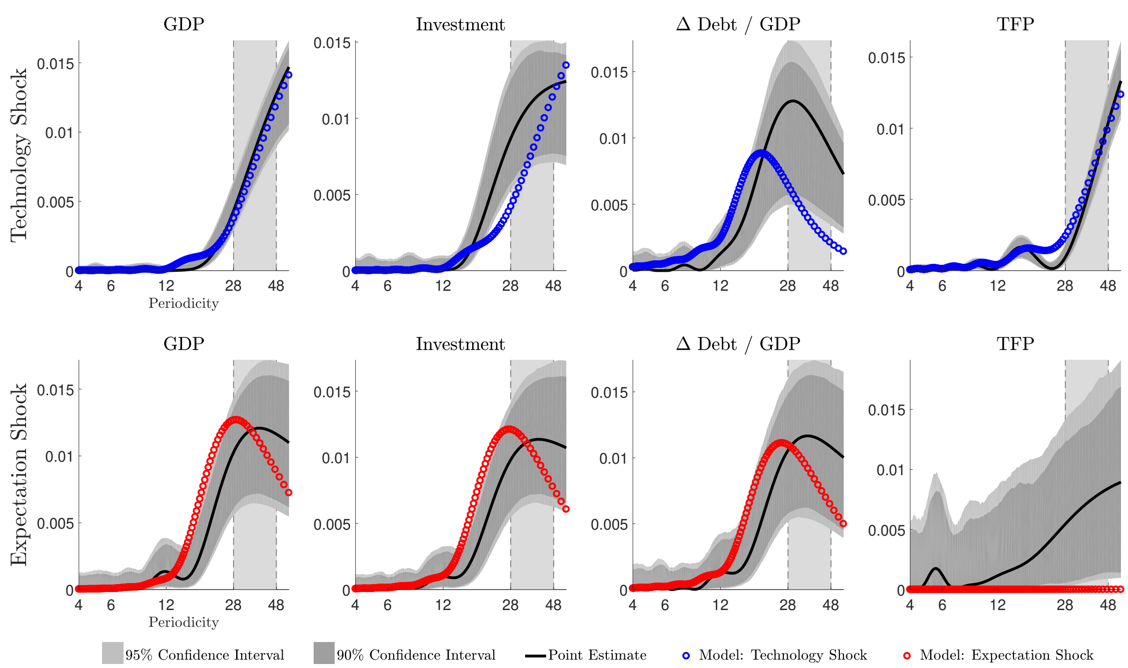


Figure 2.10: Model vs empirical spectral densities conditional on shocks

As a last validation exercise of the model, we simulate data and reproduce the results on the probability of recession presented in Figure 2.2. Figure 2.11 shows that the model can replicate the empirical probability of recession conditional on a previous expansion.

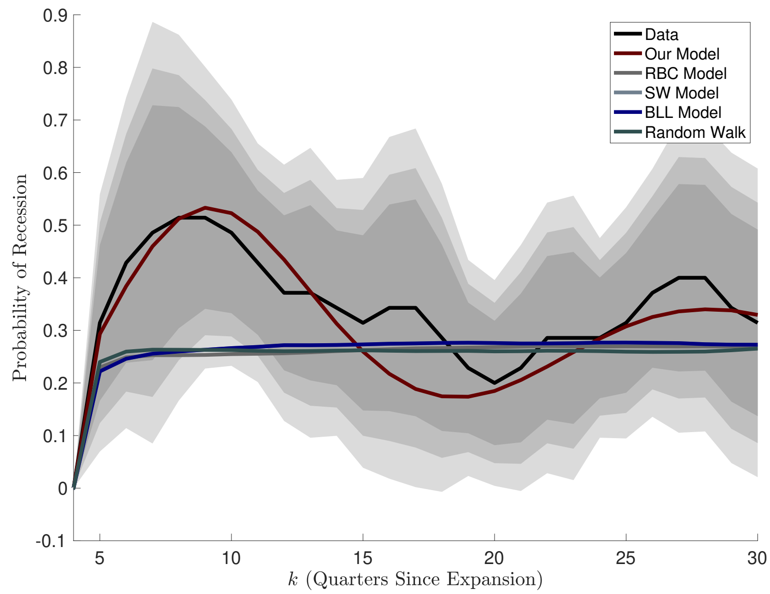


Figure 2.11: The model explains the dynamics of the recession probability

Note: Probability of recession in a two-quarter window after k quarters since expansion. Confidence intervals are 68%, 80%,and 90% (shaded areas) around the point estimate (solid black line).

2.6 Conclusions

We provide a simple synthesis of two major approaches to modeling business cycles. Under the first approach business cycles are driven by exogenous shocks that push the economy temporarily away from the long-run steady-state or balanced growth path. The second approach proposes models in which the economy experiences endogenous fluctuations even in the absence of fundamental shocks. However, both types of models fail to provide a unified explanation of the unconditional and conditional moments of the data. In the data, shocks to economic fundamentals induce dynamics that are consistent with the first view. But unconditional moments and results from expectation shocks, suggest to write models consistent with the inherent instability class. Taken together, our findings speak in favor of a theory in which both views coexist. Thus, we provide a model that embeds a strong financial amplification channel which generates boom-bust dynamics in response to i.i.d. expectation shocks. Consistent with the data, the financial amplification channel barely contributes to the propagation of technology shocks which exhibit no systematic relation between expansions and recessions. In sum, a sizeable part of economic recessions is due to preceding expansions. More importantly, those expansions that are not generated by a change in fundamentals are more likely to end in recessions. As a consequence, policy makers should intervene more decisively during expectation-driven expansions than during fundamental-driven expansions. Characterizing the optimal policy in light of our findings is part of our future endeavors.

Chapter 3

COVID-19 and Credit Constraints

3.1 Introduction

This paper investigates the economic effects of the COVID-19 outbreak and the role played by financial frictions in the transmission of the associated shocks. We take advantage of a unique survey of Italian firms' expectations and plans taken immediately before and immediately after the pandemic outbreak. This data allows us to adopt an event study approach to analyze how firms' revision in expectations over a two-month window are affected by the COVID-19 pandemic.

Our analysis addresses three main research questions. First, we ask whether credit constraints amplify the shocks associated with the outbreak and the associated government response on firms' expected sales, orders, employment, and investment. Second, we analyze the resulting changes in firms' pricing strategies and discuss how they are affected by financial frictions. In both cases, we allow for the shocks to have heterogeneous geographical and sectoral components, as well as a common component. Finally, we discuss the relative importance of supply and demand shocks, as perceived by firms at the beginning of the crisis.

Our empirical investigation exploits a unique survey on firms' expectations for sales and orders as well as plans for prices, employment, and investment. We collected this information between March 24 and April 7, 2020 — two weeks after the implementation of the first lockdown policies that followed the explosion in the number of cases and deaths. This survey covers firms in the manufacturing and production service sectors and is a special supplement to the pre COVID-19 wave of the Monitoraggio Economia e Territorio (MET) survey completed by mid-January, 2020 — one month before the official "case zero" in Italy.[1] In addition to a broad set of firms' characteristics, the pre COVID-19 MET survey contains expectations on sales and pricing strategies for the next year, together with questions on loan applications that we employ to construct firm-specific proxies of financial constraints. Our matched dataset is composed of 7,800 firms for which we have full pre and post COVID-19 information in a two-month interval around the pandemic outbreak. For approximately 5,000 of them we also have complete balance-sheet information. The availability and wealth of our dataset allow us to investigate how firms revise their expectations and plans in response to the COVID-19 outbreak, and to provide a novel perspective on the effects of the pandemic.

There are several reasons why the Italian experience is relevant and interesting. First, Italy was the first Western country to be severely hit by the pandemic, which

[1] The original dataset is fully representative of all size classes (including micro-sized companies), geographic region, and two-digit levels in the manufacturing and production service sectors.

was largely unanticipated. It was also the first country in the world to implement a national lockdown policy. Second, there is significant geographical heterogeneity in the severity of the COVID-19 outbreak with some provinces in the North being hit the hardest. In addition, there is sectoral heterogeneity due to the differential government restrictions on production that forced some firms to shut down while other firms deemed essential stayed open throughout the entire pandemic. Third, Italian firms are predominantly small and privately-held, thus a priori more likely to be credit constrained. This feature makes the Italian industrial system a particularly instructive setting to explore the role of financial frictions.

Our empirical strategy is based on the assumption that the revision in firms' expectations between the two surveys is entirely due to the COVID-19 pandemic. This assumption is reasonable because the two surveys are taken within a short time interval and no other significant event occurred during that period. For expected sales and price plans the same questions were asked in both surveys so that we can calculate the revision in expectations over approximately the same 12-month horizon. For other variables such as orders, employment, and investment, we cannot exactly control for the pre COVID-19 expectations, but we use sales anticipation to account for firms' outlook before the pandemic. Our aim is to investigate how post COVID-19 expectations are affected by financing constraints, allowing for heterogeneous geographical and sectoral components of the pandemic shocks and controlling for pre COVID-19 expectations and a wide set of firm's characteristics.

Our analysis delivers a number of important and novel results. At a descriptive level, our survey data suggests that the COVID-19 outbreak induced a significant leftward shift of the distributions for expected sales and a rightward shift for price plans. In absolute values, these changes are larger for firms that are financially constrained, classified as non-essential, or located in provinces more severely hit by the pandemic, as measured by the number of COVID-19 related deaths.

Motivated by this descriptive evidence we investigate econometrically the determinants of firms' expectations and plans in a multivariate framework. Our econometric results show that financial frictions shape the effect of the COVID-19 outbreak on firms' sales and orders expectations and on firms' employment, investment, and price plans. Credit-constrained firms display a relatively more pessimistic outlook for sales and orders, and plan to reduce employment and investment relatively more than unconstrained firms. In other words, our results suggest that financial frictions amplify the effects of the shocks generated by the COVID-19 pandemic. In addition, our evidence supports the view that credit-constrained firms plan to increase prices relatively more (or to decrease prices relatively less) than unconstrained firms. This result is consistent with a markup strategy by financially-constrained firms aimed at boosting internal sources of funds even at the cost of future losses of their customer base.

We also investigate the effect of geographical and sectoral components of the shocks generated by the COVID-19 outbreak and the associated government response. Our evidence shows that firms in areas that were more severely affected by the COVID-19 epidemic display a significantly different reaction in terms of expectations and plans. Such firms are more pessimistic in terms of future sales and orders, plan to decrease investment and employment, and to increase prices by more, relative to firms located in provinces with fewer deaths. In addition, our evidence suggests that firms that were subject to more severe restrictions, because deemed to be non-essential, have more pessimistic sales and order expectations, and plan a larger decrease in both employment and investment.

Finally, we investigate whether the COVID-19 outbreak is affecting the markup of Italian firms also for reasons other than the existence of financing constraints. In the light of theories that emphasize collusive oligopoly considerations or variations in the number of firms, we explore two additional reasons for countercyclical markups: sectoral concentration and sectoral firm dynamics.[2] Sectoral concentration or measures of firms dynamics do not appear to significantly affect firms' pricing strategy on their own. Nevertheless, credit-constrained firms located in more concentrated or more dynamic sectors plan to increase prices relatively more than their credit-constrained counterpart located in less concentrated or less dynamic sectors. We conclude that, while there is ample evidence of countercyclical markups due to credit constraints consideration, other reasons for countercyclicality do not play an important role in shaping the effect of the COVID-19 outbreak on prices. As unconstrained firms represent the vast majority (80 percent) of our sample, an increase in prices coupled with a fall in sales, orders, and investment is suggestive of the supply component of the shocks generated by the pandemic being somewhat larger than the demand component.

The structure of the paper is as follows. In Section 3.2 we discuss the related literature. Section 3.3 describes the data sources. Section 3.4 provides some descriptive

[2] See Section 3.5.4 for more details.

evidence on the effects of the COVID-19 pandemic on sales and price expectations. Section 3.5 presents the econometric results, while Section 3.6 concludes the paper.

3.2 COVID-19 outbreak: related literature

The COVID-19 outbreak generates complex and multifaceted supply and demand shocks. On the supply side, the lockdown imposed on businesses obviously represents a very large, albeit temporary, adverse labor supply shock. The restrictions imposed by the authorities on labor input mobility are also likely to increase firms' costs or decrease the efficiency of labor if, for instance, teleworking is an imperfect substitute for working on site. Moreover, the increased morbidity and mortality, even independently from lockdown measures and restrictions on mobility, affects labor supply negatively. Although the effect of morbidity and mortality, *per se*, on the labor supply may be small, the fear and concerns generated by contagion and deaths may lead to substantial reduction in labor supply because workers may decide to report sick or take time off due to this fear. On the demand side, the pandemic shock may affect consumption and saving decisions due for instance to an increase in precautionary savings and a fall in consumption as a consequence of the increase in uncertainty. Such increase can also lead to a postponement of investment projects and, therefore, to a fall in investment demand. Moreover, the disruption of supply in one sector can be felt as a demand shock for upstream firms or a negative supply shocks for downstream firms.

Not surprisingly, the economic literature on the COVID-19 outbreak is multifaceted as well, with a rapid increase in the number of papers that analyze the economic consequences of the pandemic from a micro and macro perspective. Some of the micro papers are based on firm- and household-level survey evidence.[3] Other papers rely on different data sources.[4] With regard to the role of financial factors, Acharya and Steffen (2020) show that during the COVID-19 pandemic the US stock market had higher valuations for firms with access to liquidity through cash holdings or credit lines. Ramelli and Wagner (2020) use US stock prices and corporate conference calls to show that initially investors negatively priced internationally-oriented firms. As the virus spread in Western countries, leverage and internal liquidity emerged as more important value drivers. None of the papers above does or can explore fully the effect of the COVID-19 pandemic on expectations or plans for quantities, factor demand, and prices, accounting also for financial frictions in the transmission mechanism. Moreover, the availability of expectations just before and just after the COVID-19 outbreak allows us to use the shortness of the window to identify the economic effects of the pandemic. Furthermore, we are in a unique

[3] See Bartik et al. (2020) for evidence on US small businesses' conditions and decisions, Balleer et al. (2020) on German firms' price plans and the role of demand versus supply shocks, Buchheim et al. (2020) on the effect of country-wide policy actions and local conditions on German firms' outlook and the uncertainty associated with it, and Baert et al. (2020) on Flemish employees' teleworking. See also Coibion et al. (2020) on US household labor-market experience and Briscese et al. (2020) on Italian household compliance with government mandated restrictions. Brancati and Brancati (2020) provide some evidence on the COVID-19 pandemic for innovative and international-oriented companies on the same dataset.

[4] Bekaert et al. (2020) rely on Survey of Professional Forecaster to disentangle aggregate demand and supply shocks generated by the COVID-19 outbreak. In a similar vein, Brinca et al. (2020) use sign restrictions in a structural VAR to identify the supply and demand component of the COVID-19 related shocks at a sectoral level. Andersen et al. (2020) use customer transactions from a Danish bank to analyze individuals responses. Hassan et al. (2020) develop text-based measures of costs, benefits, and risks for listed firms in a large number of countries. Baker et al. (2020) use news-paper measures of the increase in uncertainty for the US, the UK, and other countries. Finally, Caggiano et al. (2020) use a structural VAR to show how the effects of the COVID-19 induced uncertainty can be amplified by worsening in financial frictions.

position to account for firm-specific measures of financial frictions based on survey information about loan applications.

Finally, a different set of contributions has enriched standard macro models with features that capture the COVID-19 related shocks.[5] Some of these papers have a multi-sector and/or input-output structure, and allow for nominal wage rigidities and financial constraints (Baqaee and Farhi, 2020b; Faria-e Castro, 2020; Guerrieri et al., 2020; Woodford, 2020). Our empirical contribution also emphasizes the importance of sectoral heterogeneity, due, for instance, to the classification of firms as essential (non-essential), as well as the role of financial constraints in the transmission mechanism. In addition, we document the importance of spatial heterogeneity in the intensity of the COVID-19 related shocks. Moreover, we provide firm-level evidence on the relative importance of demand, cost, and markup shocks and describe the aggregate implications they give rise to. Our results can be compared with those obtained in the calibrated models we have just mentioned. In the aggregate, we document a slight increase in firms' prices, together with a large fall in sales. This result is consistent with the simulations in Baqaee and Farhi (2020b) that allow for sectoral and aggregate shocks. More broadly, our findings are consistent with those obtained in models that generate a large fall in output but a moderate price response (e.g., Eichenbaum et al., 2020a).

More generally, our paper contributes to the overall debate on the role of capital market imperfections in the amplification or mitigation of macroeconomic shocks

[5] See also Baqaee and Farhi (2020a), Basu et al. (2020), Bigio et al. (2020), Bodenstein et al. (2020), Eichenbaum et al. (2020a), Eichenbaum et al. (2020b), Fernández-Villaverde and Jones (2020), Fornaro and Wolf (2020), Kaplan et al. (2020), Krueger et al. (2020), and McKibbin and Fernando (2020).

and on the sensitivity of different types of firms to such shocks. The idea behind amplification is that when a shock occurs, the net worth of the firm (or the bank) is impacted, leading to a change in the wedge between internal and external finance and, hence, in investment and labor decisions. There has been a lively debate in the context of DSGE models on whether amplification occurs or not.[6] From an empirical standpoint, there is firm-level evidence in favor of amplification of demand shocks, such as monetary policy shocks, for firms that are more likely to be financially constrained. Moreover, there is evidence that such firms are more sensitive to shocks to banks' balance sheet and to uncertainty shocks. In this area the challenge is the identification of truly unanticipated exogenous shocks.[7] The COVID-19 event represents an ideal laboratory because it generates shocks that are exogenous and unanticipated, and this allows us to present new evidence on the role of financing constraints in the transmission of non-monetary shocks. Our evidence suggests that financing constraints enhance the effects of the shocks generated by the COVID-19 pandemic on factor demand and output decisions.

Moreover, the availability of price expectations/plans in our data is an opportunity to investigate the effect of financial constraints on firms' pricing strategies. Our

[6] The seminal papers are Bernanke et al. (1999) and Carlstrom and Fuerst (1997). The presence or absence of amplification depends upon the nature of the shock itself, the nature of the financial contract, and the parameterization of the model. See, for instance, Gertler and Karadi (2011), Carlstrom et al. (2016), and Dmitriev and Hoddenbagh (2017).

[7] The literature that bears directly or indirectly on this issue is too vast to review here. We just mention the seminal contributions by Gertler and Gilchrist (1994) using semi-aggregate data, Kashyap et al. (1994) –although the original aim of the paper was to investigate the bank-lending channel– using firm-level data. For evidence on the effects of shocks to the banking system during the financial crisis or the sovereign debt crisis, on different type of firms see Chodorow-Reich (2014) and Balduzzi et al. (2018) among others. The importance of firms' balance sheets in the transmission of consumer demand shocks during the Great Recession is emphasized in Giroud and Mueller (2017). For evidence on the effects of uncertainty shocks in presence of financing constraints see Gilchrist et al. (2014) and Alfaro et al. (2018).

findings that financially constrained firms expect to charge higher prices is consistent with previous theoretical and empirical work on the price setting of constrained firms.[8] The basic logic is that in a downturn firms find it optimal to increase prices in order to raise current liquidity, due to greater difficulties to access external finance, instead of investing in building their customer base.

In addition to financing constraints, there can be other explantions for countercyclical markups. In the context of a collusive oligopoly model, for instance, markups may be countercyclical because firms are less able to collude during booms: when demand is high, the benefit from deviating by lowering prices increases and the oligopoly must lower its markup in order to maintain discipline.[9] Moreover, when entry and exit is possible, changes in demand prociclically affect the number of firms leading to a countercyclical change in the degree of competitiveness in a sector. In periods of low demand, therefore, prices can be set higher relative to marginal cost while the opposite is true in a period of high demand.[10] Our evidence for unconstrained firms does not provide support for countercyclical markup movements due to a collusive oligopoly mechanism or the entry/exit of firms in the aftermath of the COVID-19 outbreak. More specifically, prices are not set to be higher in highly concentrated sectors or in sectors characterized by greater churning

[8] The seminal papers in the area are Gottfries (1991) and Chevalier and Scharfstein (1995). A recent important contribution providing empirical evidence in support of this mechanism is Gilchrist et al. (2017). Kim (2020), instead, provides evidence that firms affected by a negative financial shock decrease prices in the short run in order to liquidate inventories and generate additional cash flow, followed by a price increase in the medium run.

[9] Rotemberg and Saloner (1986), Rotemberg and Woodford (1991), Rotemberg and Woodford (1992), and Rotemberg and Woodford (1993).

[10] Chatterjee and Cooper (1989), Chatterjee et al. (1993), and Bilbiie et al. (2012). Bilbiie et al. (2012) also allow for an elasticity of demand that is higher in downturns using Feenstra (2003).

or mortality of firms. For credit-constrained companies there is, instead, evidence that sectoral concentration and churning affect firms' ability to set higher prices in order to boost current liquidity.

3.3 Data sources and description

Our main source of data is a firm-level survey designed to explore the consequences of the COVID-19 outbreak, combined with the 2019 wave of the MET survey on the Italian industrial system.[11] Unlike other surveys, MET provides information on every size class including micro-sized companies with less than ten employees. The survey is representative of the manufacturing sectors (60% of the sample) and the production-service industry (40%), with a total coverage of 38 NACE Rev.2 3 digit sectors.[12] Coherently with the timing of the previous waves, the administration of the 2019-survey ended in mid-January of the following year, right before the outbreak of the COVID-19 pandemic for Italy (the first reported case was on February 1, 2020). This unique characteristic makes the 2019-wave MET survey an essential source of information providing a comprehensive snapshot of firms' conditions just before entering the COVID-19 outbreak.

The original questionnaire contains a wealth of information on firms' performances and strategies, including data on direct proxies for firms' financial con-

[11] MET, *Monitoraggio Economia e Territorio*, is a private research center surveying a large number of Italian companies on a regular basis. It is one of the most comprehensive survey administrated in a single European country, with an original sample comprising seven waves – 2008, 2009, 2011, 2013, 2015, 2017, and 2019 – and roughly 25,000 observations in the cross section. The survey follows a sampling scheme representative at the firm size, geographic region, and industry levels.

[12] Production services sectors are: distributive trades, transportation and storage services, information and communication services, administrative and support service activities.

strains, bank-lending relationships, supply-chain internationalization, and R&D processes. This information is supplemented with that contained in a second survey specifically conceived to study the effect of the COVID-19 pandemic and administrated to the entire sample of respondents of the original questionnaire. This allows one to have information on both the pre and post COVID-19 expectations and plans for each company. To avoid excessive variation in the information set of the respondents, the timing of the survey was restricted in a 2-week window between March 24, and April 7, 2020. The administration started 13 days after the generalized initial lockdown imposed by the Italian government (March 11, then revised in March 22), so as to leave each firm enough time to update its beliefs and plans. This post COVID-19 survey had a final response rate of 33%, which is substantial for such a small time window, with a final number of completed interviews for about 7,800 companies. The distribution of respondents across macro-sectors, geographical macro-regions, and size-classes is similar to the one in the original survey (see Appendix B for details), but endogenous selection of the respondents is possible. We will take care of this issue by employing ex post stratification weights for the COVID-19 survey that are calibrated to reproduce the population aggregates from the sample of respondents. However, in estimation we will experiment both with weighted and unweighted data, and discuss any difference that may arise (see Section 3.5).

The post COVID-19 survey is composed of three main blocks. The first one replicates the original questions on expected changes in future sales and prices so to have the exact correspondence needed to construct a revision in firms' expectations around the COVID-19 pandemic. A second block of questions asks about firms' expectations and plans following the Coronavirus outbreak on new orders, number of workers employed, expenditure in tangible investments, expenditure in intangible investments over the next 12 months, in addition to sales growth in the following three and 12 months. These variables are effectively continuous.[13] Finally, a third block of questions directly asks about actual actions of the firms and about the difficulties in accessing credit, following the COVID-19 outbreak.

A critical issue that needs to be discussed is whether firms' expectations actually reflect the dynamic of the underlying variables they refer to. While we cannot say much on the validity of firms' beliefs after the COVID-19 outbreak, we performed a number of validation tests based on past waves of the MET survey. First of all, we exploit the panel dimension of the original dataset (between 2008 and 2019) and regress realized sales growth on the expectations held at the beginning of the period, together with province, sector, and year dummies. We show that firms' expectations are positively and significantly correlated with realized future sales, with a sizable predictive power: the R-square increases from 0.039 to 0.210 when they are included as regressors. Importantly, if we restrict the analysis only to the sovereign debt crisis period firms' expectations gain even more significance and the incremental R-squared reaches 0.333 (as shown in Table B2 of Appendix B). As for pricing plans, the lack of firm-level data on actual prices does not allow for a simi-

[13] We use the word effectively because firms were asked to provide a numerical value for expected changes below -5% or above +5%. For values within this range, they could simply indicate no change, even though some firms still provided a numerical answer. Overall, only 20% of the companies in our dataset reported a value of zero and our results are not sensible to their exclusion from the estimating sample.

lar validation exercise. However, once we aggregate firm-level expectations for the manufacturing sector (from the 2017-wave of the MET survey, closed in January 2018) we obtain an expected inflation rate of 1.39%, which is similar to the 1.1% observed inflation for domestic manufacturing goods in 2018.[14] Overall, this evidence suggests that firms' expectations are informative about the future dynamics of the actual variables, and that this is especially true in times of crisis.

In completing the dataset we will use in our empirical work, we match the firm-level surveys with 2018 official balance-sheet data (CRIF-Cribis D&B database) in order to control for predetermined firm's characteristics such as size and age. As a result of this matching, the estimating sample was reduced by roughly 35%, resulting into a final size of about 5,000 firms.[15]

Finally, we gather data on the geographical diffusion of the pandemic from official releases of the Italian Department of Civil Protection (Presidency of the Council of Minister). This data allows us to explore the consequences of the heterogeneity in the geographical diffusion of the COVID-19 outbreak.[16] In the next subsections we present details of the construction of our main measures of credit constraints, geographical exposure to the pandemic, and sectoral heterogeneity associated with the essential classification of companies. Further details on variable definitions

[14] In aggregating firm-level data we employ sampling weights to reproduce the number of companies in the population and weigh each observation for the level of sales (we will discuss the weighting again in Section 3.4.1). See https://www.istat.it/it/files//2019/03/PPI_CPP_PPS_0219_IVtrim18.pdf for the Producer Price Index. Note that, because price expectation data is available only from the 2017 wave, we cannot perform aggregate validation exercises for earlier periods.

[15] To reduce the influence of outliers, balance-sheet variables are censored at the 1% and some observations are excluded because of measurement errors (negative or nil assets, negative or nil sales).

[16] Data available from https://github.com/pcm-dpc/covid-19.

are contained in Table C.1, while summary statistics for the firm-level survey and balance-sheet data are presented in Table C.2.

3.3.1 Credit constraints

In constructing our measure for credit constraints we exploit unique information in the 2019 MET survey about bank loan applications. In particular, firms were asked if they applied for a loan in the past year and about the resulting outcome. In case of a loan application, firms were allowed to choose one of the following options: (i) the loan was granted at favorable conditions; (ii) the loan was granted at slightly less favorable conditions; (iii) the loan was granted but at very unfavorable conditions; (iv) the loan was denied. Moreover, in absence of a loan application, the questionnaire asks firms whether they did not apply because: (v) there was no need of external funds; or (vi) they knew the application would have been denied. Exploiting all this information, we have classified as credit constrained those firms that replied either (iii), (iv), or (vi) In other words, we regard a company to be constrained by banks if the loan application was rejected, accepted but at substantially worse conditions, or if the firm did not apply because it expected to be rejected. Overall, almost one fifth of the firms in our sample (18%) are classified as constrained.

We will discuss in Section 3.5.2 the relationship between our credit constraint proxy, firms' balance sheet variables, and bank relationship variables, as well as their respective role in explaining the transmission of the shocks associated with COVID-19. We conclude that our variable contains information about credit frictions that includes but goes beyond balance sheet measures of firm's riskiness and creditworthiness, as well as conventional proxies for bank-firm relationships.

3.3.2 Geographical diffusion of the pandemic

In order to explore geographical heterogeneity in the effects of the COVID-19 outbreak, we gather data on the number of positive cases in each province (107 geographical levels) and on the cumulative deaths at the regional level (20 regions). While both variables are measured with error, the number of deaths is likely to be more precise.[17] We develop a measure of local exposure by imputing the cumulated number of regional deaths to each province within a region, using the proportion of COVID-19 cases in each province. Notice that this measure captures both the perceived and actual epidemiological severity of the COVID-19 outbreak at a provincial level, as deaths and number of positive cases were at the center of the attention of all media outlets. In constructing our measure, we employed data for the day before the interview of each firm, but we also tested other timings with no significant change in our results. We have experimented using different measures of the geographical dimension of the severity of the COVID-19 outbreak and provide a discussion of the results in Footnote 28.

[17] Individuals who die due to the virus are previously admitted to the hospital and usually tested for the virus. This implies that most of the hospital deaths related to the COVID-19 are recorded. The number of deaths is subject to a downward bias because the government records a death for COVID-19 only if the patient has been tested and that is not necessarily the case when the death occurs at home or at a nursing home. However, since a large fraction of individuals who contract the virus are asymptomatic or have only mild symptoms, they are generally not tested and not recorded as positive cases. This means that the measurement error for the number of positive cases is likely to be greater than the measurement error for the number of deaths.

3.3.3 Essential vs. non-essential classification

Another dimension of heterogeneity in firms' exposure to the COVID-19 shocks is related to the regulatory restrictions on production imposed by the Italian government. While firms operating in essential sectors could remain open throughout the pandemic, companies in sectors that were considered non-essential were forced to shut down. Essential and non-essential firms are defined using the same 6-digit sectoral classification adopted by the Italian government in the decree of March 22. Moreover, main suppliers to firms in essential sectors were also allowed to stay in business and classified as essential. We can identify this additional set of companies because we have information on whether a firm stayed open despite belonging to a non-essential sector (from the COVID-19 survey). Overall, 59% of the firms in our sample were classified as essential, while 41% of the firms were subject to a forced closure during the lockdown period.

3.4 Descriptive evidence

This section presents some descriptive statistics for sales and domestic prices growth expectations/plans for the matched (with balance-sheet data) sample of 5,000 firms used in estimation. First, we report the pre and post COVID-19 unconditional distributions and discuss the aggregate implications of the outbreak. We then analyze how changes in expected sales and prices depend upon the financial status of the company or the geographical and sectoral component of the shock. We also describe the joint distribution of expected changes in sales and prices. This preliminary look at the data is meant to identify some potential factors driving the effects of the COVID-19 pandemic on sales and prices, and it is a prologue to the multivariate analysis in Section 3.5. Since we are interested in the effects of the COVID-19 outbreak on the entire economy, the descriptive evidence presented in this section employs post-stratification weights for the post COVID-19 survey that are calibrated to reproduce the overall Italian industrial structure. These weights may be only approximately correct for the 5,000 firms survey if there are further selection issues generated by matching the survey data with the balance-sheet data.[18] We will discuss this issue in Section 3.5 (see Footnote 26).

3.4.1 General consequences of the COVID-19 outbreak

We focus on sales' expectations and price plans as we can rely on two identical questions contained in the original 2019 MET survey and repeated in the March 2020 survey. The first question asks about the expected sales growth over the next 12 months. Firms were allowed to give a categorical answer on the expected change: i. very negative (less than -15%); ii. negative (between -15% and -5%); iii. stable (between -5% and +5%); iv. positive (between 5% and 15%); and v. very positive (more than 15%). As for prices, firms were directly asked for the expected (continuous) percentage change over the next 12 months.

The upper and bottom panels of Figure 3.1 present the distribution for pre and post COVID-19 expected sales growth over the next year. The leftward shift of the

[18] Unless specified otherwise, the picture from the unweighted sample is essentially in line with the one presented. The similarity is even greater when calculating the weighted statistics using the 7,800 firms sample.

distribution is quite evident, with about 80% of firms reporting either expectations of a contraction (between -5% and -15%) or of a large contraction (less that -15%) in sales. Before the COVID-19 outbreak, instead, 60% of firms expected sales to be fairly stable, with about 20% of companies forecasting future increases. Figure 3.2 shows the same expected dynamics for (discretized) domestic prices. In this case, we observe a rightward shift in the price distribution, with the unweighted mean increasing from 1.1% to 7% in the most recent survey (see also Table C.2).[19] If we weight each answer by firms' sales and by the sampling weights –that reproduce the population of companies– we obtain, instead, a moderate aggregate upward revision in expected firms' prices of thirteen basis points (from 2.48% to 2.61%). This preliminary evidence suggests that while both the demand and supply components of the shocks are playing an important role, the supply component is slightly more important in the aggregate. This moderate price response is consistent with the simulation results in Baqaee and Farhi (2020b) and Eichenbaum et al. (2020a). We will return to these issues when discussing whether the price increase is due to a rise in costs or to countercyclical markups.[20]

Note, however, that behind this aggregate figure there is a very heterogeneous experience across individual firms. This heterogeneity extends to the correlation between expected sales and price changes, as can be seen by calculating the joint distribution of prices and sales changes. In the first panel of Table 3.1 we report the

[19] The Kolmogorov-Smirnov test indicates that we can reject the hypothesis of identical pre and post distributions for expected sales and prices growth with a p-value approximately equal to zero. Some care should be used in interpreting the result for sales because of the reduced accuracy of the test with a categorical variable.

[20] See Sections 3.4.2, 3.5.2, and 3.5.4.

percentage of firms, over the entire sample, indicating price increases, stability, or decreases conditional on the categorical expectations for sales. A plurality of firms indicate that they expect a decrease in sales and an increase in prices (32.7%). This represents almost half (44.9%) of the firms that expect sales to decrease. The percentage of those indicating no price changes or negative price changes and a fall in sales are smaller but still sizable: 24.7% and 15.4%, respectively (33.9% and 21.1% of the firms expecting a decrease in sales). This means that, whereas most of the firms expect a decrease in sales (72.8%), the price response to the COVID-19 outbreak is heterogeneous. This suggests that the relative importance of demand and supply shocks differs across types of firms. We will explore this heterogenity in the descriptive statistics that will follow and in our econometric analysis.

Finally, Figure 3.3 shows the discretized distribution of sales expectations over the next three months together with sales expectations over the next 12 months calculated from the continuous measures of sales provided by the supplemental post COVID-19 survey. The two distributions show that the COVID-19 shock is associated with a fall in expected sales at all horizons. In addition, the expected decrease in sales over the next three months (-23.9%) is larger that in the next 12 months (-19.3%). This implies that firms in our sample expect a steep initial fall followed by a very slow recovery. We obtain the same qualitative results when we use the expected fall in sales weighted with their initial level and with sample weights (-15.5% and -10.2%, respectively). We conclude that over this time horizon there is evidence of very asymmetric V-shaped expectations or a L-shaped rotated few degrees counter-clock wise.

3.4.2 Role of financial frictions

This subsection provides some preliminary evidence on how financial frictions affect firms' sales and price expectations in the aftermath of the COVID-19 outbreak. The upper panel of Figure 3.4 reports the post COVID-19 distributions for both types of firms' sales expectations. More than 60% of financially-constrained firms expect sales to decrease by more than 15% versus around 45% of unconstrained firms. The comparable histograms for domestic price plans is shown in the bottom panel of Figure 3.4. Although visually it is not easy to detect a change, the average increase in expected price for financially-constrained firms is 8.2%, while for financially unconstrained firms is only 6.8%.[21] This represents *prima facie* evidence of different pricing decisions depending upon the severity of financial frictions.[22] This picture is confirmed if we look at the joint distribution of expected sales and price changes. The percentage of firms expecting price increases when sales are expected to decrease is higher for credit-rationed firms: 42.5%, versus 32.7% for the entire sample (see Table 3.1 Panel 2).

3.4.3 Geographical and sectoral heterogeneity

In this subsection we present some descriptive evidence on the geographical and sectoral heterogeneity of the COVID-19 outbreak and on its effects. Figure 3.5 dis-

[21] The Kolmogorov-Smirnov test indicates that we can reject the hypothesis of identical revisions of sales and price growth expectations between financially constrained and financially unconstrained firms (p-value of less than 1%).

[22] Note that the differences between credit and not credit-constrained firms are much smaller for pre COVID-19 expectations. We do not report the figures for reason of space. A similar remark applies when we partition the sample by firms located in area with a high number of deaths and essential/non-essential firms.

plays the heterogeneity in the number of cumulative deaths across the Italy. While some provinces in the North suffered from a large number of deaths, the pandemic was significantly less severe in Central and Southern regions, although there is substantial variation also within these macro areas. In the top panel of Figure 3.6 we exploit this geographical heterogeneity to further explore the effect of the COVID-19 outbreak on expected sales growth, depending upon the level of exposure to the pandemic. High exposure is defined as being located in a province in the top quartile of the distribution of deaths. In high mortality areas, firms are more pessimistic about sales than in provinces with lower exposure (53.4% vs. 47.2% expect a fall in sales below 15%). Although we do not present the graph, prices are expected to increase more in areas with high exposure to COVID-19: the average expected change is 9.3% versus 6.2% in low exposure areas. Moreover, the percentage of firms planning price increases when sales are expected to decrease is higher for firms located in high COVID-19 death area: 41.5%, versus 32.7% for the entire sample (see Table 3.1 Panel 4).

In the bottom panel of Figure 3.6 we report the post COVID-19 expectations of future sales for essential and non-essential firms. Non-essential firms are on average more pessimistic than essential companies: 52.7% of firms that shut down expect a fall in sales greater than 15%, while only 38.6% of essential firms expect such a large fall. As for prices, there is no evidence of a significant difference in the average expected change for essential and non-essential companies.[23] The percentage of

[23] The Kolmogorov-Smirnov test suggests that the revision in sales growth is significantly different for essential versus non-essential firms, while it is not significantly different for the exposure to deaths. The caveat of using the Kolmogorov-Smirnov test for categorical variables still applies. For the

firms planning price increases when sales are expected to decrease is somewhat higher for essential firms: 35.6%, compared to 32.7% in the entire sample (see Table 3.1 Panel 7).

3.4.4 Firms' actual response to the shock

Although the emphasis of the paper is on firms' expectations and plans, it is also interesting to briefly discuss the actions they have taken or were forced to take in response to the COVID-19 outbreak.

Figure 3.7 shows the percentage of firms that: (i) adopted teleworking; (ii) temporarily reduced employment or (iii) hours worked; were in (iv) complete or (v) partial shutdown; (vi) applied for government programs. Firms were allowed to choose up to three categories in the list. Importantly, almost 50% of the firms decided to temporarily shut down (this is also a result of the restrictions imposed by the government) while only a negligible fraction of them have been willing to partially shut down. Note that we use the information on not shutting down in non-essential sectors to finesse our definition of who is classified as an essential firm. In addition, a large group of firms (30.9%) adopted teleworking, and more firms opted for reducing the hours worked (21.4%) rather than reducing the level of employment (12.1%). The more prevalent use of reductions in hours most likely reflects the fact that firms would rather avoid separating permanently from their employees. The use of teleworking by firms raises the issue of its efficiency relative

revision of prices across our geographical or sectoral partition, we cannot reject the hypothesis that the two distributions are identical.

to on-site work. If the two modes are not perfect substitutes moving to teleworking constitutes an adverse cost shock.

3.5 Econometric strategy and results

In our empirical work we take advantage of the availability of pre and post COVID-19 expectations for sales and prices (at a one-year horizon) to model the revision in firms' expectations around the COVID-19 outbreak in Italy, that was largely unanticipated. For other continuous variables, such as sales over the next three months, orders, employment, and investment over the next 12 months, we do not have the correspondent expectations formed before the COVID-19 episode. In this case, we will use past expectations for sales to control for the pre COVID-19 information set. Recall that the two surveys where taken only two months apart and, therefore, we assume that they reflect expectations in the yearly growth rate over approximately the same time horizon. The short length of the interval also motivates our assumption that the pandemic is the dominant factor in determining firms' expectation revisions.

In specifying our estimating equation, we assume that the innovation in expectations about marginal net returns generated by the shocks described above is the sum of: a common component η_t; a component that is proportional to the log of one plus the number of deaths at a provincial level, $\text{Deaths}_{i,t}$; and a component that reflects the essential or non-essential status of the firm, $\text{Essential}_{i,t}$. We assume that the effect of these three components on a firm's decisions depend upon whether or not it was credit constrained at time $t-1$, $\text{CC}_{i,t-1}$. More specifically, our empirical estimation will be based on variants of the following model:

$$\begin{aligned}&\mathbb{E}^i(y_{i,t+1}|\text{post COVID-19}) - \mathbb{E}^i(y_{i,t+1}|\text{pre COVID-19}) = \alpha(\text{CC}_{i,t-1})\eta_t \\ &+ \beta_1(\text{CC}_{i,t-1})\text{Deaths}_{i,t} + \beta_2(\text{CC}_{i,t-1})\text{Essential}_{i,t} + \gamma' x_{i,t-1} + \lambda_s + \lambda_r + \varepsilon_{i,t}\end{aligned} \tag{3.1}$$

where $y_{i,t+1}$ represents the growth rate of sales, prices, orders, employment, investment in tangible assets, and investment in intangible assets of firm i between periods t and $t+1$; and $\mathbb{E}^i(y_{i,t+1}|\mathcal{I})$ denotes the expectations formed by firm i on $y_{i,t+1}$ with information set $\mathcal{I} = \{\text{pre COVID-19}, \text{post COVID-19}\}$.

In the model we also control for a set of firms' characteristics and initial conditions $x_{i,t-1}$. We will start from a simple specification where $x_{i,t-1}$ is composed of the log of total assets ($\text{Size}_{i,t-1}$), log of one plus age ($\text{Age}_{i,t-1}$), and of log of population at the provincial level ($\text{Population}_{i,t-1}$). The inclusion of $\text{Population}_{i,t-1}$ is meant to make certain that $\text{Deaths}_{i,t}$ does not simply capture the demographic size of the province. In a robustness exercise we also include log provincial value added per capita as a proxy for local productivity and the log number of blood donation per capita as a proxy for social capital, and show that our results for $\text{Death}_{i,t}$ are robust to their inclusion (see the Online Appendix). We also include the pre COVID-19 expectations ($\mathbb{E}^i[y_{i,t+1}|\text{pre COVID-19}]$) to allow the cross-sectional difference in expectation revisions to be related to the initial outlook of the firm. Finally, in a richer specification, we augment the model with a set of dummies indicating whether firm i is importing ($\text{Import}_{i,t-1}$), exporting ($\text{Export}_{i,t-1}$), part of a group ($\text{Group}_{i,t-1}$), family run ($\text{Family}_{i,t-1}$), and investing in R&D ($\text{R\&D}_{i,t-1}$), as well as a continuous variable indicating the percentage of graduate employees ($\text{Graduate}_{i,t-1}$).[24] In all specifications we also include 88 two-digit sector dummies, λ_s, and 20 region fixed effects, λ_r, to account for several sources of sectoral and geographical heterogeneity. Note that the inclusion of a rich set of industrial controls, together with some of the firm-specific measures in $x_{i,t-1}$ (especially size, age, R&D, and internationalization), also capture most of the firms' ability to substitute on-site work with telework.

The inclusion of these controls can be rationalized in two non-mutually-exclusive ways: (a) there may be an additional component of the shock that varies with such firms' characteristics, or (b) the response to the common shocks depends upon such characteristics. Conditional on $x_{i,t-1}$ and the region (λ_r) and sector (λ_s) dummies, we assume that the error term $\varepsilon_{i,t}$ in Equation 3.1, that captures other unobservable components generated by the COVID-19 pandemic, approximation errors, and measurement errors, is uncorrelated with $\text{CC}_{i,t-1}$, $\text{Deaths}_{i,t}$, and $\text{Essential}_{i,t}$. Under these assumptions, the coefficient on these variables can be estimated consistently.

We estimate our model both with the unweighted and the weighted sample, using the ex post stratification weights for the COVID-19 survey. We use the weighted results as our benchmark throughout the main body of the paper, but present in the Online Appendix the results from the unweighted sample and discuss in the text any difference between the two. On the whole, the results are similar with a limited number of exceptions. We focus on the weighted estimates for two reasons. First, we want results to be as representative as possible of the effects of the

[24] The subscript $t-1$ indicates variables from 2018 balance-sheets (the last available) or from the pre COVID-19 MET survey.

COVID-19 outbreak on the overall Italian economy. Second, the weighting scheme assuages concerns about causal inference due to the possible endogenous selection of companies in the sample. The latter may be induced by the very administration of the COVID-19 survey that was concentrated in a short time window during the lockdown. If firms that were less affected by the pandemic, such as those in essential sectors or located in areas with lower deaths, had a higher probability of being sampled and if this selection is correlated with the error terms, the post-estimation weights may help achieving consistency of the estimates (see Solon et al., 2015 for a discussion and further references).[25] As we have noted before, the post-stratification weights were calibrated to reproduce the aggregate population starting from the full set of 7,800 firms interviewed in the COVID-19 survey. Because we focus on the subsample of 5,000 firms with complete balance-sheet data, the weighted analysis may still not be perfectly representative of the manufacturing and productive services sector.[26]

The structure of the section is as follows. In Sub-section 3.5.1 we present results for a model where the effect of the geographical and sectoral components ($\text{Deaths}_{i,t}$ and $\text{Essential}_{i,t}$, respectively) do not depend on initial financial conditions. This im-

[25] The comparison of weighted and unweighted descriptive statistics in Table C.2 provides, indeed, some evidence in favor of an oversampling of companies that were less exposed to the pandemic shock. We also tested the need of sampling weights with the statistic proposed by DuMouchel and Duncan (1983). The test speaks in favor of a weighted estimation because weights and their interactions with the independent variables add significant explained variance to the overall model (p-values are virtually zero).

[26] A Probit model of the probability of appearing in the matched 5,000 sample, conditional on being in the 7,800 firms sample, suggests that the number of deaths does not affect significantly such probability, but being essential increases it, while being financially constrained decreases it. Some of the controls, such as size, are also significant. This suggests that in the estimating sample, relative to the 7,800 firms sample and conditional on the controls, we have firms that in same dimensions (for instance, essential status and financial constraints) tend to be less severely affected by the pandemic.

plies that β_1 and β_2 are assumed to be constant. In Sub-section 3.5.2 we further explore the role of financing constraints during the COVID-19 outbreak, using this baseline model. In Sub-section 3.5.3 we relax the assumption on β_1 and β_2 and test whether the effects of $\text{Deaths}_{i,t}$ and $\text{Essential}_{i,t}$ depend on pre COVID-19 credit constrains, $\text{CC}_{i,t-1}$. Finally, in Sub-section 3.5.4 we add further interactions to discuss additional evidence of the role of markup changes.

3.5.1 Results from the baseline model

The results presented in this section are based on estimates of the following model:

$$\begin{aligned}\mathbb{E}^i(y_{i,t+1}|\text{post COVID-19}) = \delta\,\mathbb{E}^i(y_{i,t+1}|\text{pre COVID-19}) + \alpha_0 + \alpha_1\text{CC}_{i,t-1} \\ + \beta_1\text{Deaths}_{i,t} + \beta_2\text{Essential}_{i,t} + \tilde{\gamma}'\tilde{x}_{i,t-1} + \lambda_s + \lambda_r + \varepsilon_{i,t}\end{aligned} \tag{3.2}$$

Note that Equation 3.2 is a re-parameterization of Equation 3.1 in which we have moved the pre COVID-19 expectations to the right-hand side. Its coefficient δ equals one plus the element of γ associated with the pre COVID-19 expectations in Equation 3.1. Now, $\tilde{x}_{i,t-1}$ denotes the firms' characteristics excluding the $\mathbb{E}^i(y_{i,t+1}|\text{pre COVID-19})$. In addition, the essential restriction imposed in this equation is that β_1 and β_2 do not depend on firms being financially constrained. Moreover, for notational simplicity we have subsumed η_t into α_0 and α_1.

The first two columns of Table 3.2 contain the results of OLS models for the one-year ahead expected sales growth (numbered from one to five according to increasing levels of optimism). Columns 3 and 4 report the estimates for ordered logit models for the same variable, while in column 5 we employ the categorical revision in expectations as an alternative dependent variable (post-pre COVID-19).[27] For the first two models, we present both a narrow and wide set of control variables $\tilde{x}_{i,t-1}$, while, for the last models, we present results only with the wide set of controls. In all specifications, the geographical component of the shocks generated by the COVID-19 outbreak plays a significant role, as firms located in a province with a higher number of deaths are affected more negatively than firms in areas with lower exposure. Our interpretation is that the more severe effects are related both to the innovation in the actual and perceived severity of the crisis, as reflected in the reported number of deaths and positive cases.[28] Moreover, the negative effect of the COVID-19 event is significantly attenuated if the firm is classified as essential. This result underlines the importance of the restrictive measures on production taken by the Italian government in shaping the economic effect of the COVID-19 outbreak.

Importantly, firms that were credit constrained before the outbreak are significantly more pessimistic about their future sales. This is consistent with firms

[27] In this case, we define nine order categories based on the number of steps the revision can take. For instance, going from the expectation of a change in prices between minus/plus 5% to being very pessimistic (less than -15%) is a two step negative change.

[28] We have experimented with several measures of the geographical intensity of the COVID-19 outbreak, in addition to the log of the imputed number of deaths at the provincial level. For instance, we have tested whether log deaths and log population have coefficients which are equal in absolute value and with opposite signs, in which case we could enter the log mortality rate as the only regressor. We cannot reject this restriction for expected sale growth, but we reject it for expected price growth. For this reason we have decided to present the specification in which the restriction is not imposed. Moreover, we have also replaced the reported number of deaths with the number of actual deaths in excess of those that occurred in the same month over the past ten years, which may be a better measure of the actual mortality associated with COVID-19. This variable, independently from how it is entered, is never significant, suggesting that part of the effects of $\text{Deaths}_{i,t}$ reflects the fact that the number of deaths and cases (which we used in imputing to the province level the regional number of deaths) were the figures that received the greater attention in the media. See Table B3 in Appendix C.2 for detailed results. In addition, in the Online Appendix we report a set of results using the log of one plus the number of reported provincial cases as opposed to $\text{Deaths}_{i,t}$. Our basic conclusions still hold but the coefficients are somewhat less precisely estimated than the ones using $\text{Deaths}_{i,t}$.

decreasing employment and investment due to the financial frictions they face and, hence, decreasing production. This could be also consistent with financially-constrained firms expecting lower price growth, but we will show below that this is not the case. All these results are robust to the choice of the set of control variables. Given the categorical nature of the variables, it is not straightforward to make statements about the size of the effects. We will do so later in Table 3.4 when we use continuous variables.[29]

In the first four columns where the dependent variables are the expectations formed after the outbreak the sign of the coefficient of the categorical variable suggests that firms with more pessimistic (optimistic) pre COVID-19 expectations are more (less) likely to be pessimistic about post COVID-19 expected sales. In the fifth column the sign of past expectations is reversed –as one would expect– because the dependent variable is the revision in expectations. As for the other controls, larger firms hold more optimistic expectations about sales. Given size, however, younger firms are more optimistic about the future. The latter result is possibly linked to the higher dynamism and capability of adaptation of young companies. Finally, export-oriented firms hold more pessimistic expectations, possibly because of the global nature of the COVID-19 pandemic, as well as the protectionist and other restrictive measures adopted by national governments.

In Table 3.3 we analyze the effect of the COVID-19 event on domestic price plans. In terms of included regressors, this specification is similar to the one in Table 3.2,

[29] As a robustness check, we also run a multinomial logit model and the overall message is very similar to one obtained in the case of the ordered logit model. See Table B4 in Appendix C.2.

with the exception of having included lagged expected price changes, as opposed to lagged sales growth, as a control. Since price expectations are continuous, we only estimate an OLS specification. Also in this case, deaths at the province level and credit constraints play an important role for domestic prices: everything else equal, prices tend to be higher in provinces with a higher death rate or for financially constrained firms. The positive coefficient on $\text{Deaths}_{i,t}$ is consistent with supply shocks being more important relatively to demand shocks in the geographical component of the COVID-19 generated shocks. We have also included the essential status of the firm, but its coefficient is never significant. This is somewhat surprising because one might have thought that essential firms faced a less unfavorable cost shocks compared to the non-essential ones. Among the additional controls, size is the only variable that matters for domestic prices, while other variables are statistically not significant.

Quantitatively, as deaths are expressed in units of standard deviation, the results imply that a one-standard deviation increase in the log of deaths (approximately five deaths) raises price growth by approximately 2.5 percentage points. Moreover, a credit-rationed firm will increase price growth between four and six additional percentage points compared to its non-rationed counterpart. This result is consistent with previous theoretical and empirical work with price setting of financially constrained firms. The basic logic is that financially-constrained companies are more likely to put a premium on liquidity as opposed to building up the customer base by charging lower prices (see the seminal papers by Gottfries, 1991 and Chevalier and Scharfstein, 1995, and the recent contribution by Gilchrist et al., 2017).[30]

In the regression model is somewhat surprising that past price plans are not significant. Since the price variable is continuous, we have also tried a specification in which the dependent variable is the difference between the post and pre COVID-19 price plans. Results are reported in column three of the table and the results confirm the conclusions we have reached so far.

In order to explore in more details the effects of the COVID-19 pandemic, we now move to Table 3.4 where we present OLS estimates for the same specification of Table 3.2, but using a wider set of dependent variables: expected sales at three and 12 months, expected orders, as well as plans for employment, investment in tangibles, and investment in intangibles. These variables allow us to make more precise statements regarding the quantitative effect of the COVID-19 pandemic as they are effectively continuous and expressed in percentage points changes with respect to the pre COVID-19 situation.

Overall, the estimates broadly confirm the results discussed so far. The number of COVID-19 deaths has a negative and significant effect on short-term and long-term sales expectations, but has a sizable impact also on orders and employment. Everything else equal, a one-standard deviation increase in the (log) number of provincial deaths leads to a reduction in firms' expected sales growth of additional 1.7 percentage points, both in the short and in the long run. Similarly, the essential

[30] See also Asplund et al. (2005), de Almeida (2015), Kimura (2013), Lundin et al. (2009), and Montero and Urtasun (2014) for additional evidence supporting this mechanism. Kim (2020), instead, provides evidence that firms facing an adverse financial shock reduce prices in the short run to liquidate inventories and generate cash flow, followed by a price increase in the medium run.

designation is associated with significantly less negative outcomes, with a reduction in the expected fall in sales of approximately ten percentage points.

Most importantly, being credit constrained negatively and significantly affects all the variables, with only the investment in tangibles being significant at the 10% level. The effect of financial frictions is particularly important over the next three months, with a fall in expected sales for credit-constrained firms that is 15% greater than the one for unconstrained companies. This difference is somewhat reduced over the 12-months horizon, although it is still quite sizable (8%). Note that the inclusion of past sales expectations as a control is perfectly appropriate for sales expectations at 12 months and approximately so for the other dependent variables. In terms of the additional controls, the important role of size and, sometimes, age for many of the dependent variables is confirmed. Finally, the coefficients of family ownership, import, or export status are very rarely significant.

Our results are robust to several variations. First of all, unweighted analyses broadly confirm our conclusions, with a few exceptions that is worth highlighting (see the Online Appendix, Tables C1-C3). While the effect of Deaths$_{i,t}$ is still positive and sizable for prices, the effects on the other dependent variables are insignificant in this framework. Note, however, that Deaths$_{i,t}$ will play a role for expected sales even in the unweighted sample when interacted with credit constraints, as we will discuss in Section 3.5.3. Moreover, the negative effect of Essential$_{i,t}$ becomes more significant in the price equation. In addition, results are also robust to: (i) removing from the dataset the firms that did not report an actual figure for the minus/plus five percent categories of the effectively continuous variables, instead of imputing to them a value of zero; (ii) using a common information set on $\text{Deaths}_{i,t}$ for all firms (i.e., the imputed provincial deaths in the day that preceded the start of the survey); (iii) controlling for provincial measures of social capital (log number of blood donations per capita) and productivity (log value added per capita); (iv) defining essential nature of the firms based on the March 11, 2020 government classification instead of March 22, 2020 classification; and (v) clustering at the industry level as opposed to the province level. See the Online Appendix for detailed results.

3.5.2 More evidence on financial constraints

In this section we provide additional evidence on the role of financial factors and bank relationship in investment, employment, and output decisions, and on the determinants of financing constraints.

In Table 3.5 we replace the pre COVID-19 credit constraint dummy with a set of firm-level balance-sheet variables and survey information on the nature of the firm-bank relationship. More specifically, we introduced the past share of liquid assets ($\text{Liquidity}_{i,t-1}$), cash flow ($\text{Cash Flow}_{i,t-1}$), the ratio between fixed assets and total assets ($\text{Tangible Assets}_{i,t-1}$), leverage ($\text{Leverage}_{i,t-1}$), and net accounts payable ($\text{Trade Credit}_{i,t-1}$). Moreover, we also include the number of lender banks ($\text{N of Lender Banks}_{i,t-1}$), the length of the relationship with the main bank ($\text{Lending Relationship years}_{i,t-1}$), and the distance from the latter ($\text{Distance Lender Bank}_{i,t-1}$). Across all dependent variables, the strongest association is with the stock of liquid assets: firms that entered the pandemic outbreak with greater liquidity tend to have more favorable expectations and plans. Its effect is significant for sales expectations at three and 12 months, orders, and employment. Interestingly, the coefficient of liquidity is larger for expectations at a three-month horizon, emphasizing firms' need of financial slack in order to survive and deal with the COVID-19 shock in the short run. Liquidity is only significant at the 10% level for investment in intangibles and not significant for tangible investments. The role of liquidity as a buffer against falls in net revenue is very relevant from a policy perspective, as it underscores the importance of lending facilities that provide liquidity to firms.

As for the other regressors, their effects are mostly non-significant. One exception is asset tangibility, for which there is a sizable and significant positive association with sales expectations over the next 12 months, and of the length of lending relationship that is significantly and positively associated with sales expectations over a three-month horizon. The coefficient on leverage is mostly non-significant at conventional levels, with the exception of the equation for employment where it has a positive sign. A possible explanation for this fact is that leverage may not only capture financial fragility, but may also be an indicator of access to credit. Finally, the variable $\text{Essential}_{i,t}$ is significant at the 1% level across all the dependent variables, while $\text{Deaths}_{i,t}$ remains strongly significant for sales over the next three and 12 months and orders, but less so for employment.

If we include the financial variables together with our proxy for financing constraints (all of them are lagged), the latter remains largely significant in almost all specifications, while the former is not, with the exception of asset tangibility (see the Online Appendix for detailed results).[31] When we also include bank relationship variables (in which case the sample diminishes because they are available only for a subset of the firms) the same result holds. We conclude that our proxy for credit constraints does not merely summarize firms' financial variables, but it also contains information that goes beyond firm's riskiness and creditworthiness as reflected by their balance sheets and other observables, such as size and age, and even proxies for bank-firm relationships.

In Table 3.6 we investigate the determinants of being credit constrained *after* the pandemic outbreak using a linear probability model. The dependent variable is a dummy that equals one if in the COVID-19 survey the firm mentions credit constraints as one of the main adverse factors it faces. The regressors are lagged firms' financial variables, bank relationship variables, pre COVID-19 proxy for credit constraints, and other controls. Again, having liquidity at the end of 2018 is negatively associated with a probability of being financially constrained and so is cash flow received during the year. In the more general specification, highly-leveraged companies have a significantly larger probability of being credit rationed after the pandemic, while the ability to obtain trade credit reduces the likelihood of being constrained.[32] There is also persistence in the credit-constrained status in the sense that past credit constraints (measured from the 2019 MET survey) increase the probability of being constrained in the COVID-19 crisis, while bank-relationship

[31] Our proxy for financing constraints is significant only at the 10% level in the base equation for prices, but it is significant at the 1% level for non-essential firms in the interacted model.

[32] Giannetti et al. (2011) suggest that trade credit is a relatively cheap form of finance for many Italian firms. Their findings also challenge the idea that the use of trade credit signals the inability to access bank credit.

variables do not appear to play an important role. The coefficient on $\text{Deaths}_{i,t}$ remains strongly significant while the essential status does not seem to have an effect, which is somewhat surprising.

Overall, our evidence highlights the critical role of liquidity either for the probability of being constrained or for firms' expectation and plans. Our results are consistent with the evidence in Acharya and Steffen (2020) who show that during the COVID-19 pandemic the US stock market had a higher valuation for firms with access to liquidity through cash holdings and credit lines. Our evidence is also in line with Ramelli and Wagner (2020) who stress the role of leverage and internal liquidity as important value drivers following the COVID-19 outbreak. Finally, our results are consistent with the general message in Jeenas (2018) who highlights liquidity as an important determinant of the transmission of monetary policy to firms' investment decision: firms with more liquid assets decrease investment less in response to a contractionary monetary policy shock. All these results provide support for the policy prescription discussed in Draghi (2020) who emphasizes the importance of providing liquidity facilities to firms in the aftermath of the COVID-19 pandemic to avoid a deep recession. They are also supportive of the policy actions by the Italian government that provide a guarantee for lending by banks to domestic firms.

3.5.3 Model with interactions

We now explore a richer specification of our model that allows for interactions between financing constraints, the local severity of the COVID-19 pandemic, and the essential designation of the firm. Adding these interactions allows the effect of credit constraints to differ geographically, as captured by deaths at the provincial level, or by sectors as captured by the essential dummy (or later by other sector characteristics such as concentration and firms' entry and exit). The estimated equation is now:

$$\begin{aligned}
&\mathbb{E}^i(y_{i,t+1}|\text{post COVID-19}) = \delta\,\mathbb{E}^i(y_{i,t+1}|\text{pre COVID-19}) + \alpha_0 + \alpha_1\text{CC}_{i,t-1} \\
&+ \beta_{1,0}\text{Deaths}_{i,t} + \beta_{1,1}\text{CC}_{i,t-1} \times \text{Deaths}_{i,t} + \beta_{2,0}\text{Essential}_{i,t} + \beta_{2,1}\text{CC}_{i,t-1} \times \text{Essential}_{i,t} \\
&+ \tilde{\gamma}'\tilde{x}_{i,t-1} + \lambda_r + \lambda_s + \varepsilon_{i,t}
\end{aligned} \tag{3.3}$$

In Tables 3.7, 3.8, and 3.9 we reproduce the specifications of the models in Tables 3.2, 3.3, and 3.4 with additional interaction terms. For sales, prices, and expectations about factor demand the coefficients of these interaction terms tend to be mostly not significant, which justifies our choice to start from the simpler version of the model. Our fundamental conclusions are largely confirmed. Nevertheless there are some very interesting exceptions. In particular, the coefficient of the interaction between credit constraints and essential is significant in the ordered logit model for sales, and in the continuous model for investment in tangibles and intangibles. The coefficient of the interaction term between credit constraints and deaths is significant for the expectation of sales over the next three months. There is, therefore, evidence that financing constraints amplify also the geographical or sectoral component of the shocks. As far as prices are concerned, the geographical dimension of the pandemic does not appear to be important in determining the effect of credit constraints, while being essential reduces the effect of credit constraints on prices.

A possible explanation is that non-essential firms expect to be in worse financial shape and plan to have higher prices in order to generate liquidity.

If we compare these results with unweighted estimates, our conclusions are again mostly unchanged. Note that in this case Deaths$_{i,t}$, when interacted with credit constraints, plays a role for expected sales over the three-month horizon. In addition, in the price equation, the coefficient of credit constraints interacted with Deaths$_{i,t}$ is now significant, while the impact of the interaction of credit constraints with Essential$_{i,t}$ is not significant (see the Online Appendix, Tables C4-C6).

3.5.4 More on markup changes and COVID-19

So far, we have emphasized the role of credit constraints in the transmission of the shocks and showed that constrained firms reduce sales and factor demand and increase prices more in the aftermath of the COVID-19 outbreak. As discussed in Section 3.2, financing constraints is just one of the mechanisms that lead to a countercyclical markup. Another explanation can be based on collusive oligopoly models. In that case, markups may be countercyclical because firms are less likely to collude during booms: when demand is high the benefit from deviating from the collusive equilibrium increases, hence the latter can only be supported if prices and markups are low (Rotemberg and Saloner, 1986; Rotemberg and Woodford, 1991; Rotemberg and Woodford, 1992; Rotemberg and Woodford, 1993). Moreover, when entry and exit is possible, the markup may be countercyclical because changes in the number of firms over the cycle affect the degree of competitiveness in a sector. Therefore, in periods of low demand prices may rise relatively to marginal cost, while the opposite can occur in a boom (Chatterjee and Cooper, 1989; Chatterjee et al., 1993; Bilbiie et al., 2012).

In order to assess whether these explanations for countercyclical markup are in play in the aftermath of the COVID-19 episode, we conduct a set of empirical exercises. Since the collusive oligopoly story is likely to be more relevant for concentrated sectors, we ask whether the coefficient of the sector dummies are significantly related to measures of concentration such as the Herfindahl-Hirschman Index in 2018 (HHI).[33] We start by focusing on the second column of Table 3.8 and document that the coefficients of the sector dummies are significantly different from one another (the p-value of this hypothesis is virtually zero). We then regress the estimates of the two-digit effects on the HHI index and show that industrial concentration is not significantly associated with the coefficients of the sectoral dummies (the t-statistic equals -0.34). Similarly, there is no significant relationship between the coefficients of the sectoral dummies and the demographic characteristics of a sector. For instance, when we use churning (defined as the sum of exits and new entries in 2018 as a proportion of the initial number of firms) in this regression its coefficient is not significant (the t-statistic equals 0.01).[34] The same is true if we employ the mortality rate, instead, as the relevant measure of firms' dynamics during the downturn generated by the COVID-19 crisis. Finally, we do not find any effect even when we test the joint significance of HHI and churning (the p-value

[33] Note that the main effect of the concentration index at the two-digit level is captured by the sector dummies. The HHI index is computed at the two-digit level on the universe of firms with balance sheets in 2018.

[34] We computed two-digit demographic indices (churning and mortality rate) from the universe of registered companies in the 2018 Infocamere database.

of the f-test equals 0.939). Therefore our analysis provides no evidence in favor of a direct effect of these two mechanisms on the markup in the aftermath of the COVID-19 outbreak.

As an additional exercise, we ask whether concentration or firms' dynamics affect the role of financing constraints in firms' pricing strategies. In Table 3.10 we explore a richer specification of Equation 3.3 that allows also for the interaction of financing constraints with concentration and churning in the sector in which the firm operates. We find that credit-constrained firms in more concentrated markets tend to have relatively higher price increases compared to their credit-constrained counterparts in less concentrated markets. This is probably because those firms find it easier to increase prices to boost liquidity in markets where they have greater market power. Analogously, credit-constrained firms in markets with more churning plan to rise prices relatively more. A way to rationalize this result is that firms operating in a sector with higher probability of exit discount the future more and are more willing to lose a share of their customers in order to boost current liquidity.

As neither concentration nor firm churning explain the effect of the sector dummies, it appears that increases in the markup for firms that are not financially constrained is not the reason for expected price increases following the COVID-19 pandemic. Note that this set of firms represent the vast majority in our sample (82%). Since in the aggregate we observe a mild increase in inflation, taken together these results suggest that the increase in cost is marginally more important than the decrease in demand. It is likely that the COVID-19 crisis generated a substantial increase in cost through several channels, as well as a large fall in demand, leading to moderate price changes. This result is consistent with the calibrated macro models such as Baqaee and Farhi (2020b) and Eichenbaum et al. (2020a) that generate a large fall in output and a moderate response of prices. Our evidence is also largely consistent with those obtained by Bekaert et al. (2020) and Brinca et al. (2020) who show the importance of both supply and demand shocks in determining the response to COVID-19 outbreak using structural VAR models.

3.6 Conclusions

In this paper we analyze the effects of the Coronavirus outbreak on Italian firms using unique survey data on pre and post COVID-19 expectations and plans. The anticipated negative economic effect of the pandemic is amply confirmed. The COVID-19 event is associated with a decrease in expected sales (at all horizons), orders, employment, and investment, and with a large fraction of firms expecting to charge higher prices.

There is strong evidence pointing to the importance of financial frictions in amplifying the effects of the shocks associated with the COVID-19 outbreak: credit-constrained firms hold more pessimistic expectations about future sales and orders, and plan to reduce employment and investment more, relatively to unconstrained firms. In addition, those firms expect to increase prices more than firms that suffer less from financial frictions. The search for and availability of liquidity is a key determinant of firms' plans in the aftermath of the negative shocks associated with the Coronavirus pandemic. Moreover, our evidence shows that firms in areas more severely affected by the COVID-19 epidemic and considered non-essential display more pessimistic expectations and plans. Finally, it appears that expected increases in markups following the COVID-19 epidemic for firms that are not financially constrained (the vast majority of firms) is not the reason why we observe an increase in prices. Thus, the large fall in sales and in factor demand, together with the moderate increase in prices that we have observed is likely to be the result of the COVID-19 crisis generating negative supply shocks that are quantitatively slightly more important than the negative demand shocks.

There is much more to learn about the effects of the COVID-19 outbreak on firms' strategies and decisions. Its effect will be felt not only on quantity and prices but also on the very organization of the firm and on the nature of its relationship with other firms. One important topic worth investigation is the effect of the COVID-19 pandemic on the supply chain and on its domestic and international structure. Another is its effect on the firms' pricing strategies in export markets. These topics are part of our research agenda, but they are left for future analysis.

3.7 Figures

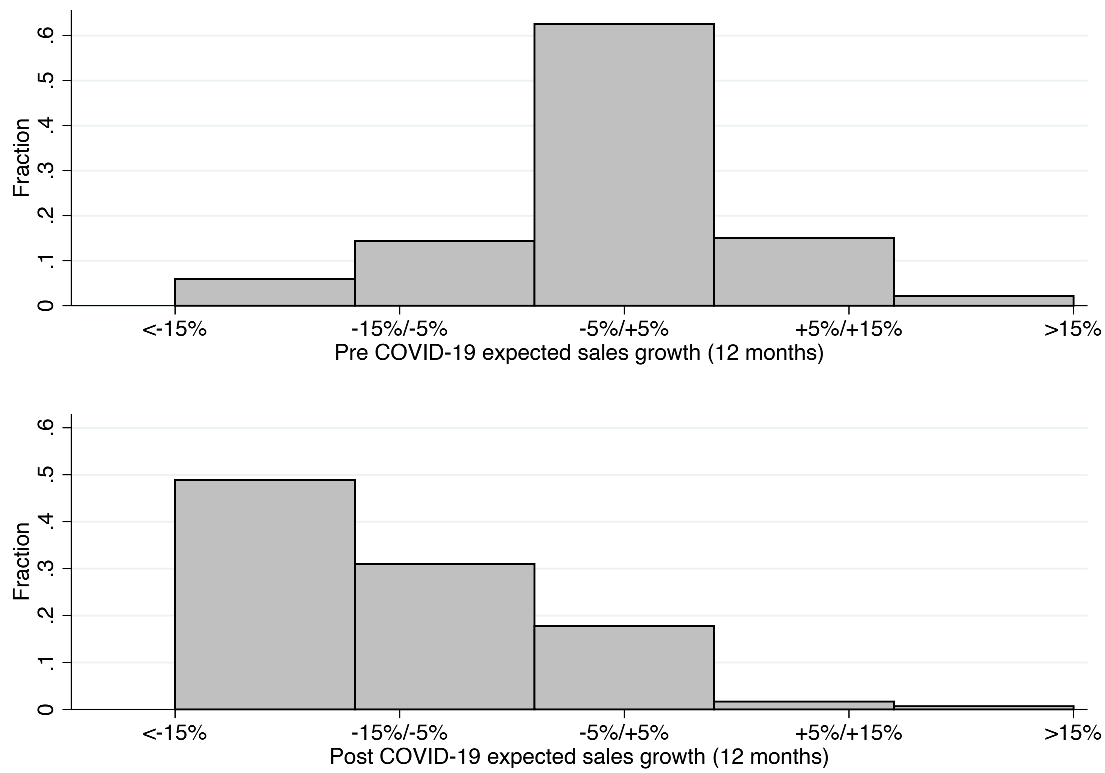


Figure 3.1: Pre and post COVID-19 expected sales growth

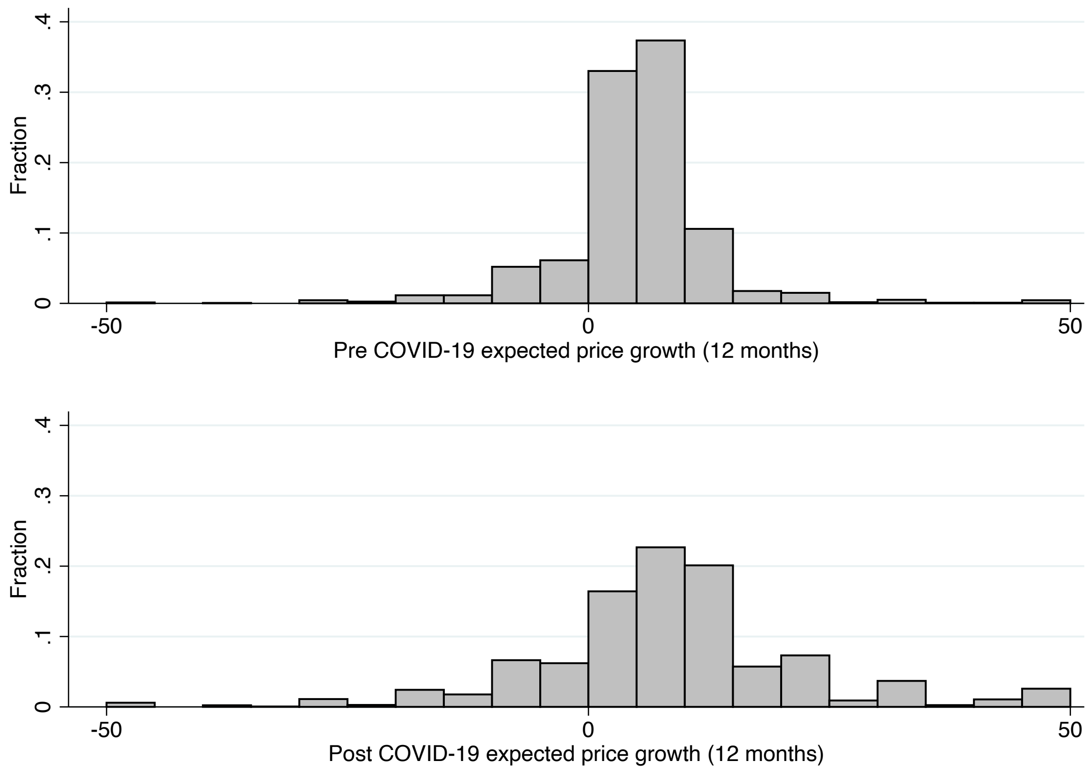


Figure 3.2: Pre and post COVID-19 expected price growth

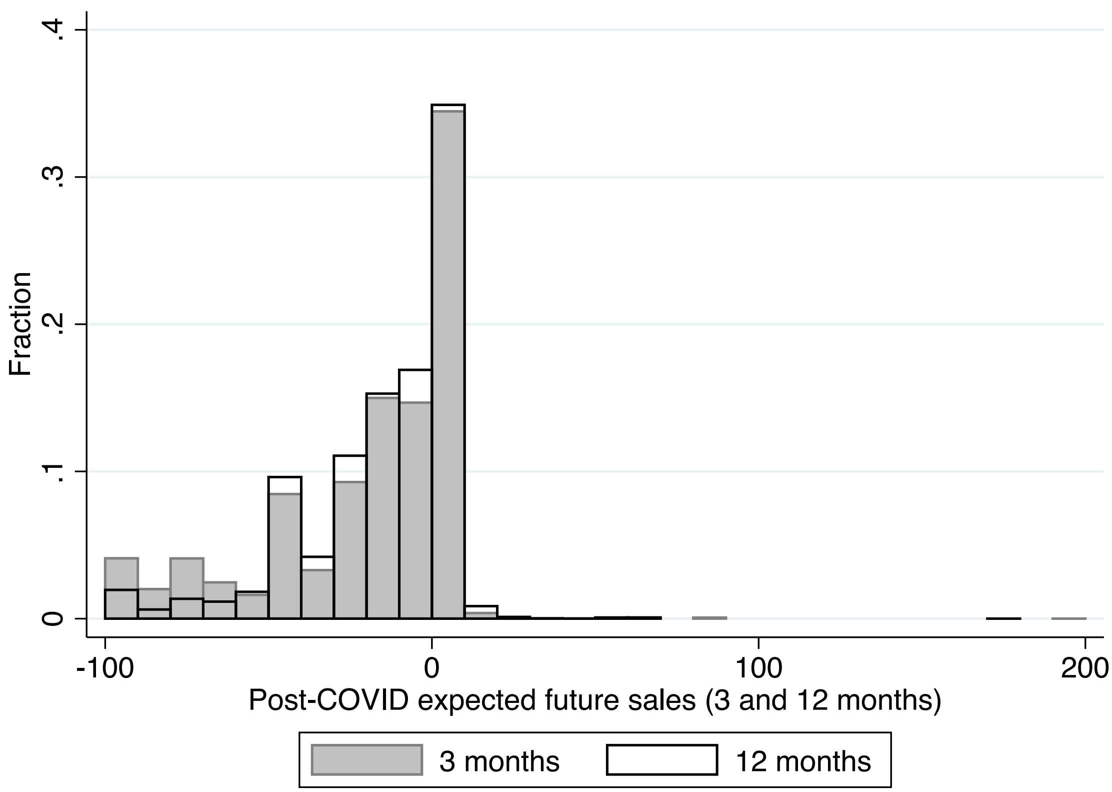


Figure 3.3: expected sales growth at three and 12 months

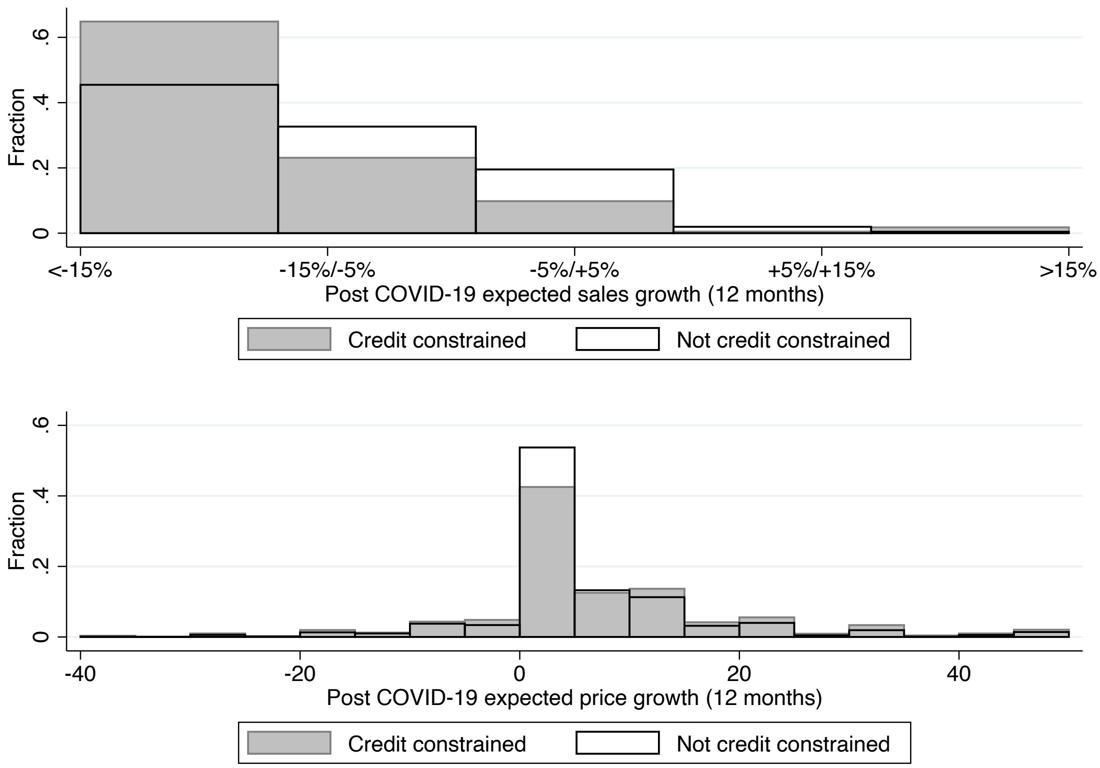


Figure 3.4: Post COVID-19 expected sales and price growth by credit-constrained status

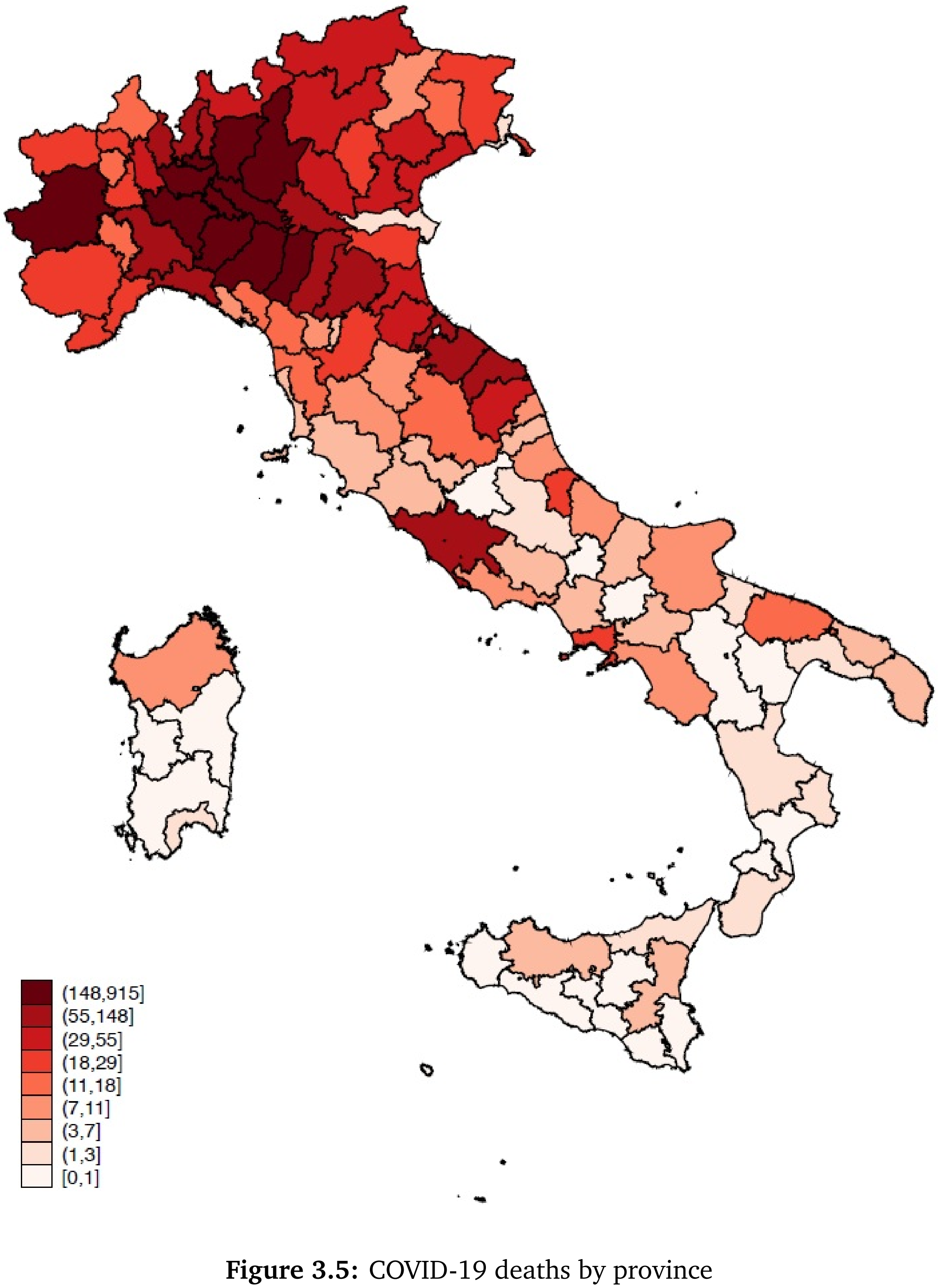


Figure 3.5: COVID-19 deaths by province

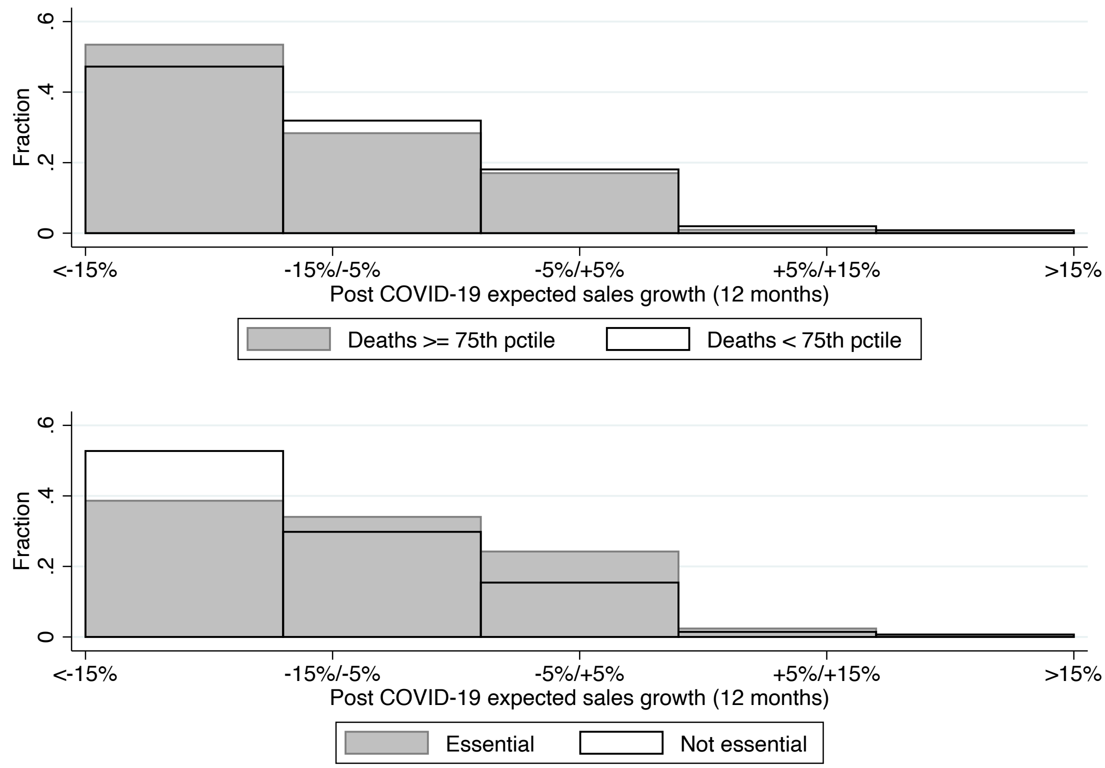


Figure 3.6: Post COVID-19 expected sales growth by Deaths and by Essential designation

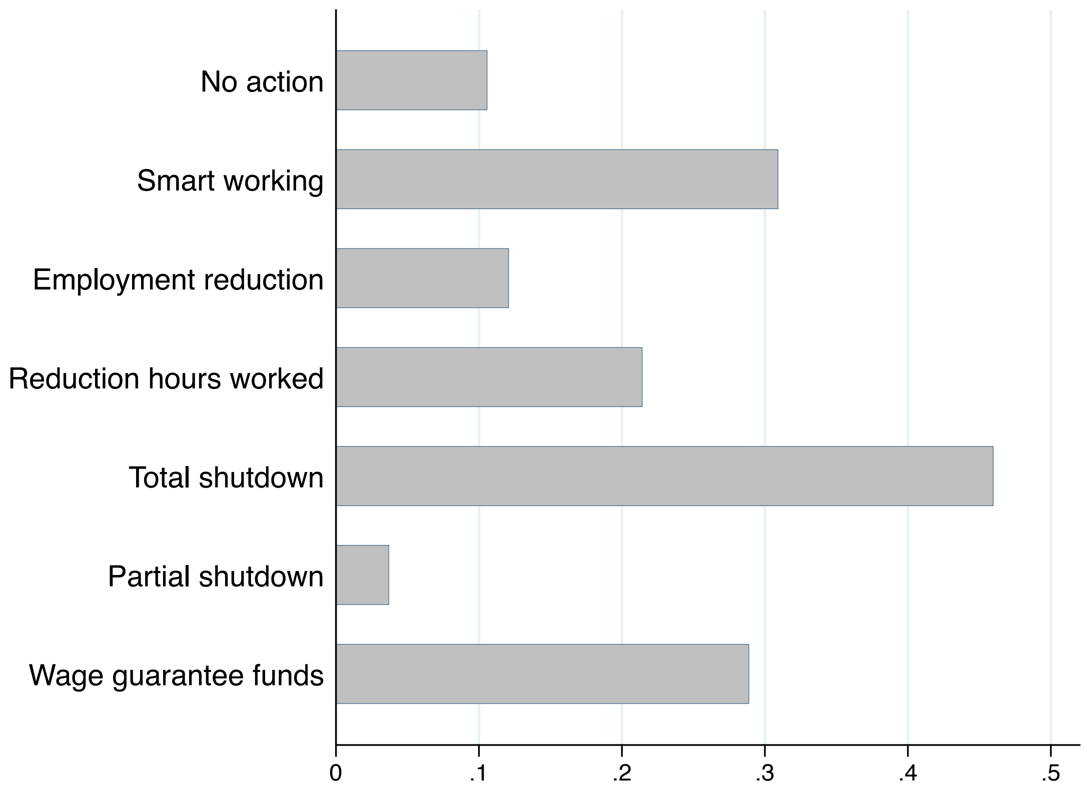


Figure 3.7: Measures adopted in response to COVID-19 outbreak

3.8 Tables

Table 3.1: Joint distribution of revision in expected sales and price growth

	Entire sample		
	$\Delta^R\mathbb{E}_{i,t}(\mathrm{P}^g) < 0$	$\Delta^R\mathbb{E}_{i,t}(\mathrm{P}^g) = 0$	$\Delta^R\mathbb{E}_{i,t}(\mathrm{P}^g) > 0$
$\Delta^R\mathbb{E}_{i,t}(\mathrm{Sales}^g 1\mathrm{Y}) < 0$	15.4%	24.7%	32.7%
$\Delta^R\mathbb{E}_{i,t}(\mathrm{Sales}^g 1\mathrm{Y}) = 0$	5.97%	10.6%	7.02%
$\Delta^R\mathbb{E}_{i,t}(\mathrm{Sales}^g 1\mathrm{Y}) > 0$	0.57%	1.32%	1.58%
	Credit constrained		
	$\Delta^R\mathbb{E}_{i,t}(\mathrm{P}^g) < 0$	$\Delta^R\mathbb{E}_{i,t}(\mathrm{P}^g) = 0$	$\Delta^R\mathbb{E}_{i,t}(\mathrm{P}^g) > 0$
$\Delta^R\mathbb{E}_{i,t}(\mathrm{Sales}^g 1\mathrm{Y}) < 0$	17.3%	15.6%	42.5%
$\Delta^R\mathbb{E}_{i,t}(\mathrm{Sales}^g 1\mathrm{Y}) = 0$	5.79%	9.13%	6.02%
$\Delta^R\mathbb{E}_{i,t}(\mathrm{Sales}^g 1\mathrm{Y}) > 0$	1.04%	2.03%	0.65%
	Not credit constrained		
	$\Delta^R\mathbb{E}_{i,t}(\mathrm{P}^g) < 0$	$\Delta^R\mathbb{E}_{i,t}(\mathrm{P}^g) = 0$	$\Delta^R\mathbb{E}_{i,t}(\mathrm{P}^g) > 0$
$\Delta^R\mathbb{E}_{i,t}(\mathrm{Sales}^g 1\mathrm{Y}) < 0$	15.1%	26.4%	31.0%
$\Delta^R\mathbb{E}_{i,t}(\mathrm{Sales}^g 1\mathrm{Y}) = 0$	5.99%	10.9%	7.20%
$\Delta^R\mathbb{E}_{i,t}(\mathrm{Sales}^g 1\mathrm{Y}) > 0$	0.49%	1.19%	1.74%
	Deaths >= 75th pctile		
	$\Delta^R\mathbb{E}_{i,t}(\mathrm{P}^g) < 0$	$\Delta^R\mathbb{E}_{i,t}(\mathrm{P}^g) = 0$	$\Delta^R\mathbb{E}_{i,t}(\mathrm{P}^g) > 0$
$\Delta^R\mathbb{E}_{i,t}(\mathrm{Sales}^g 1\mathrm{Y}) < 0$	13.6%	23.6%	41.5%
$\Delta^R\mathbb{E}_{i,t}(\mathrm{Sales}^g 1\mathrm{Y}) = 0$	4.28%	6.47%	5.23%
$\Delta^R\mathbb{E}_{i,t}(\mathrm{Sales}^g 1\mathrm{Y}) > 0$	0.34%	1.30%	3.58 %
	Deaths < 75th pctile		
	$\Delta^R\mathbb{E}_{i,t}(\mathrm{P}^g) < 0$	$\Delta^R\mathbb{E}_{i,t}(\mathrm{P}^g) = 0$	$\Delta^R\mathbb{E}_{i,t}(\mathrm{P}^g) > 0$
$\Delta^R\mathbb{E}_{i,t}(\mathrm{Sales}^g 1\mathrm{Y}) < 0$	16.1%	25.2%	29.2%
$\Delta^R\mathbb{E}_{i,t}(\mathrm{Sales}^g 1\mathrm{Y}) = 0$	6.65%	12.3%	7.74%
$\Delta^R\mathbb{E}_{i,t}(\mathrm{Sales}^g 1\mathrm{Y}) > 0$	0.66%	1.33%	0.76%
	Essential		
	$\Delta^R\mathbb{E}_{i,t}(\mathrm{P}^g) < 0$	$\Delta^R\mathbb{E}_{i,t}(\mathrm{P}^g) = 0$	$\Delta^R\mathbb{E}_{i,t}(\mathrm{P}^g) > 0$
$\Delta^R\mathbb{E}_{i,t}(\mathrm{Sales}^g 1\mathrm{Y}) < 0$	14.1%	24.7%	31.0%
$\Delta^R\mathbb{E}_{i,t}(\mathrm{Sales}^g 1\mathrm{Y}) = 0$	7.67%	12.4%	6.55%
$\Delta^R\mathbb{E}_{i,t}(\mathrm{Sales}^g 1\mathrm{Y}) > 0$	0.39%	1.75%	1.38%
	Not essential		
	$\Delta^R\mathbb{E}_{i,t}(\mathrm{P}^g) < 0$	$\Delta^R\mathbb{E}_{i,t}(\mathrm{P}^g) = 0$	$\Delta^R\mathbb{E}_{i,t}(\mathrm{P}^g) > 0$
$\Delta^R\mathbb{E}_{i,t}(\mathrm{Sales}^g 1\mathrm{Y}) < 0$	17.5%	24.8%	35.6%
$\Delta^R\mathbb{E}_{i,t}(\mathrm{Sales}^g 1\mathrm{Y}) = 0$	3.22%	7.82%	7.78%
$\Delta^R\mathbb{E}_{i,t}(\mathrm{Sales}^g 1\mathrm{Y}) > 0$	0.87%	0.62%	1.91%

Notes: $\Delta^R\,\mathbb{E}_{i,t}(\mathrm{Sales}^g 1\mathrm{Y})$ denotes the revision in pre and post COVID-19 expectations for sales growth; $\Delta^R\,\mathbb{E}_{i,t}(\mathrm{P}^g)$ denotes the revisions in pre and post COVID-19 expectations for firm-level price growth. Both variables refer to the 12-month horizon forecast.

Table 3.2: Baseline Model for Expected Sales Growth

Model	OLS		Ordered Logit		
Dependent variable:	$\mathbb{E}_{i,t}(\text{Sales}^g 1\text{Y})$	$\mathbb{E}_{i,t}(\text{Sales}^g 1\text{Y})$	$\mathbb{E}_{i,t}(\text{Sales}^g 1\text{Y})$	$\mathbb{E}_{i,t}(\text{Sales}^g 1\text{Y})$	$\Delta^R\mathbb{E}_{i,t}(\text{Sales}^g 1\text{Y})$
	(1)	(2)	(3)	(4)	(5)
Deaths	-0.0484***	-0.0466***	-0.123**	-0.122**	-0.118**
	[0.0180]	[0.0177]	[0.0551]	[0.0554]	[0.0524]
Essential	0.407***	0.396***	1.140***	1.123***	1.111***
	[0.0508]	[0.0535]	[0.148]	[0.160]	[0.149]
Credit constrained	-0.194**	-0.187**	-0.668**	-0.667**	-0.553**
	[0.0834]	[0.0774]	[0.293]	[0.273]	[0.225]
$\mathbb{E}_{i,t-1}(\text{Sales}^g 1\text{Y})$: Very Negative	-0.290**	-0.306***	-1.051*	-1.118*	4.661***
	[0.117]	[0.116]	[0.603]	[0.595]	[0.391]
$\mathbb{E}_{i,t-1}(\text{Sales}^g 1\text{Y})$: Negative	-0.356***	-0.353***	-1.173***	-1.155***	1.553***
	[0.0738]	[0.0715]	[0.273]	[0.261]	[0.187]
$\mathbb{E}_{i,t-1}(\text{Sales}^g 1\text{Y})$: Positive	0.0633	0.0720	0.176	0.206	-2.623***
	[0.0670]	[0.0714]	[0.172]	[0.190]	[0.250]
$\mathbb{E}_{i,t-1}(\text{Sales}^g 1\text{Y})$: Very Positive	0.356**	0.371*	0.635	0.702	-5.018***
	[0.178]	[0.189]	[0.412]	[0.448]	[0.619]
Size	0.120***	0.124***	0.332***	0.345***	0.348***
	[0.0172]	[0.0182]	[0.0530]	[0.0565]	[0.0524]
Age	-0.111***	-0.101***	-0.328***	-0.304***	-0.287***
	[0.0330]	[0.0317]	[0.0967]	[0.0942]	[0.0962]
Population	0.0198	0.0188	0.0378	0.0296	0.0354
	[0.0319]	[0.0318]	[0.0978]	[0.0987]	[0.0917]
Import		-0.00289		0.0341	0.0109
		[0.0651]		[0.190]	[0.188]
Export		-0.210***		-0.634***	-0.640***
		[0.0573]		[0.169]	[0.161]
Group		0.108		0.257	0.346
		[0.107]		[0.302]	[0.311]
Family Firm		-0.0941		-0.223	-0.228
		[0.0649]		[0.181]	[0.187]
% Graduated Empl.		-0.00117		-0.00356	-0.00358
		[0.00103]		[0.00299]	[0.00302]
R&D		0.0710		0.195	0.180
		[0.0653]		[0.194]	[0.180]
Region FE	✓	✓	✓	✓	✓
Industry (2 Digit) FE	✓	✓	✓	✓	✓
R-squared (Pseudo R2)	0.257	0.270	(0.145)	(0.153)	(0.244)
N obs.	5008	5008	5008	5008	5008

Notes: $\mathbb{E}_{i,t}(\text{Sales}^g 1\text{Y})$ denotes the post COVID-19 expectations for sales growth over a 12-month horizon. For the definition of the explanatory variables see Table C.1. Weighted OLS and ordered logistic estimates. Standard error (in square brackets) clustered at the province level. *, **, *** indicate statistical significance at the 10%, 5%, and 1%, respectively.

Table 3.3: Baseline Model for Expected Price Growth

Dependent variable:	$\mathbb{E}_{i,t}(\mathrm{P}^g)$	$\mathbb{E}_{i,t}(\mathrm{P}^g)$	$\Delta^R\mathbb{E}_{i,t}(\mathrm{P}^g)$
	(1)	(2)	(3)
Deaths	2.662***	2.529***	2.805***
	[0.889]	[0.815]	[0.840]
Essential	-1.813	-2.189	-2.578
	[2.668]	[2.485]	[2.705]
Credit constrained	4.412**	4.480**	5.801***
	[1.969]	[2.005]	[2.081]
$\mathbb{E}_{i,t-1}(\mathrm{P}^g)$	0.122	0.134	
	[0.0893]	[0.0933]	
Size	-1.016***	-0.880**	-1.030***
	[0.345]	[0.371]	[0.363]
Age	-0.833	-0.712	-0.350
	[1.039]	[1.110]	[1.083]
Population	0.704	0.607	0.644
	[0.788]	[0.797]	[0.827]
Import		-1.051	-0.951
		[1.158]	[1.189]
Export		-1.982	-2.212
		[1.596]	[1.590]
Group		0.313	0.464
		[1.350]	[1.220]
Family Firm		-0.303	-0.271
		[1.130]	[1.143]
% Graduated Empl.		0.0392	0.0463
		[0.0327]	[0.0316]
R&D		-1.894	-1.819
		[1.207]	[1.163]
Region FE	✓	✓	✓
Industry (2 Digit) FE	✓	✓	✓
R-squared	0.185	0.197	0.209
N obs.	4886	4886	4886

Notes: $\mathbb{E}_{i,t}(P^g)$ denotes the post COVID-19 expectations for firm-level price over a 12-month horizon. For the definition of the explanatory variables see Table C.1. Weighted OLS estimates. Standard error (in square brackets) clustered at the province level. *, **, *** indicate statistical significance at the 10%, 5%, and 1%, respectively.

Table 3.4: Baseline Model for Continuous Measures for Sales, Orders, Employment, and Investment

	(1) $\mathbb{E}_{i,t}(\text{Sal}^g\text{3M})$	(2) $\mathbb{E}_{i,t}(\text{Sal}^g\text{1Y})$	(3) $\mathbb{E}_{i,t}(\text{Ord}^g)$	(4) $\mathbb{E}_{i,t}(\text{Emp}^g)$	(5) $\mathbb{E}_{i,t}(\text{Tan}^g)$	(6) $\mathbb{E}_{i,t}(\text{Int}^g)$
Deaths	-1.774***	-1.731***	-1.933***	-1.571**	-1.554	-0.260
	[0.614]	[0.452]	[0.481]	[0.664]	[1.250]	[0.740]
Essential	10.45***	8.900***	6.733***	4.495**	10.41***	8.706***
	[1.768]	[1.586]	[1.742]	[1.741]	[2.838]	[2.325]
Credit constrained	-14.86***	-7.856***	-10.17***	-7.830**	-4.878*	-5.556**
	[3.600]	[2.361]	[2.746]	[3.073]	[2.586]	[2.235]
$\mathbb{E}_{i,t-1}(\text{Sales}^g\text{1Y})$: Very Negative	-10.59*	-15.22***	-13.56**	-14.48***	-21.15***	-15.33**
	[6.347]	[5.376]	[5.651]	[5.251]	[7.716]	[7.350]
$\mathbb{E}_{i,t-1}(\text{Sales}^g\text{1Y})$: Negative	-3.365	-13.15***	-14.44***	-6.536**	-12.49***	-10.32***
	[5.477]	[3.925]	[3.994]	[2.654]	[3.646]	[3.448]
$\mathbb{E}_{i,t-1}(\text{Sales}^g\text{1Y})$: Positive	6.804	0.439	-2.762	-0.756	-7.633**	-3.681
	[4.479]	[2.707]	[2.817]	[2.460]	[2.962]	[2.747]
$\mathbb{E}_{i,t-1}(\text{Sales}^g\text{1Y})$: Very Positive	7.965*	1.571	-1.391	0.544	-3.839	-4.677
	[4.600]	[3.106]	[3.097]	[2.487]	[3.064]	[3.273]
Size	3.007***	2.775***	2.504***	0.887***	1.228*	0.892
	[0.580]	[0.573]	[0.410]	[0.324]	[0.635]	[0.632]
Age	-1.724**	-2.289**	-2.727***	0.245	-0.602	2.199
	[0.861]	[0.937]	[0.971]	[1.355]	[1.033]	[1.411]
Population	-1.108	-0.971	-0.192	-1.431*	-0.876	-1.443
	[1.209]	[1.228]	[1.407]	[0.858]	[1.027]	[0.987]
Import	-3.535*	-1.329	0.0889	-2.042	-2.620	-1.093
	[2.083]	[1.526]	[1.717]	[1.287]	[2.511]	[2.755]
Export	-5.090***	-1.586	-1.596	0.439	-3.165	-2.180
	[1.775]	[1.541]	[2.004]	[1.217]	[2.834]	[2.243]
Group	-0.0153	0.386	-2.613	1.389	1.960	2.374
	[2.616]	[2.616]	[2.408]	[1.405]	[2.248]	[2.143]
Family Firm	-1.734	-2.492*	-1.930	-1.007	-1.759	-0.800
	[1.536]	[1.303]	[1.385]	[1.341]	[2.195]	[2.130]
% Graduated Empl.	0.0446	-0.00703	0.000901	-0.0130	-0.0233	0.0451*
	[0.0306]	[0.0283]	[0.0270]	[0.0333]	[0.0289]	[0.0266]
R&D	-0.0632	-0.201	-3.057*	2.852**	-1.322	2.712
	[1.756]	[1.331]	[1.745]	[1.416]	[2.506]	[1.703]
Region FE	✓	✓	✓	✓	✓	✓
Industry (2 Digit) FE	✓	✓	✓	✓	✓	✓
R-squared	0.317	0.309	0.272	0.262	0.200	0.197
N obs.	5008	5007	5007	5007	5004	5003

Notes: $\mathbb{E}_{i,t}(Y)$ denotes the post COVID-19 expectations for variable Y. Sal3M^g denotes expected sales growth at a three-month horizon, Sal1Y^g denotes expected sales growth at a 12-month horizon. Ord^g, Emp^g, Tan^g, and Int^g denote the 12-month growth rate for orders, employment, investment in tangible assets, and investment in intangible assets. For the definition of the explanatory variables see Table C.1. Weighted OLS estimates. Standard error (in square brackets) clustered at the province level. *, **, *** indicate statistical significance at the 10%, 5%, and 1%, respectively.

Table 3.5: Financial Constraints and firms' expectations and plans: using Firms' Financial Variables

	(1) $\mathbb{E}_{i,t}(\text{Sal}^g 3\text{M})$	(2) $\mathbb{E}_{i,t}(\text{Sal}^g 1\text{Y})$	(3) $\mathbb{E}_{i,t}(\text{Ord}^g)$	(4) $\mathbb{E}_{i,t}(\text{Emp}^g)$	(5) $\mathbb{E}_{i,t}(\text{Tan}^g)$	(6) $\mathbb{E}_{i,t}(\text{Int}^g)$
Deaths	-1.623**	-1.469**	-2.080***	-1.800***	-1.266	0.297
	[0.810]	[0.619]	[0.679]	[0.656]	[1.198]	[0.870]
Essential	11.02***	9.137***	6.700***	4.732***	10.84***	8.709***
	[1.587]	[1.648]	[1.862]	[1.598]	[2.938]	[2.521]
Liquidity	8.112***	5.275**	8.010***	5.804**	4.388	4.451*
	[2.370]	[2.329]	[2.468]	[2.901]	[2.962]	[2.473]
Cash Flow	-7.683	0.373	1.673	11.19*	-3.093	-3.710
	[6.728]	[4.740]	[5.358]	[5.982]	[6.989]	[7.455]
Tangible Assets	4.563	7.925**	5.229	-0.113	2.523	-0.384
	[4.930]	[3.369]	[3.889]	[4.547]	[5.502]	[4.472]
Leverage	-0.0747	-0.0592	0.0805*	0.107**	-0.0412	-0.000812
	[0.0647]	[0.0631]	[0.0475]	[0.0526]	[0.0735]	[0.0626]
N of Lender Banks	-3.722	-1.380	-2.209	-2.393	-0.988	1.150
	[2.811]	[2.785]	[2.830]	[2.001]	[3.236]	[2.590]
Lending Relationship (Years)	3.321**	0.796	1.696	1.566	0.284	0.577
	[1.478]	[1.308]	[1.695]	[1.185]	[1.592]	[1.462]
Distance lender bank	-0.162	0.742	-0.396	-0.0489	0.425	0.961
	[0.692]	[0.660]	[0.654]	[0.946]	[0.857]	[0.840]
Trade Credit	-1.688	-5.250	1.852	3.452	0.313	-6.311
	[5.213]	[4.962]	[5.109]	[3.930]	[5.831]	[7.177]
Region FE	✓	✓	✓	✓	✓	✓
Industry (2 Digit) FE	✓	✓	✓	✓	✓	✓
Wide controls	✓	✓	✓	✓	✓	✓
R-squared	0.325	0.320	0.272	0.294	0.200	0.195
N obs.	4709	4708	4708	4708	4705	4704

Notes: For variable definition see Table 3.4. For the definition of the explanatory variables see Table C.1. Weighted OLS estimates. Standard error (in square brackets) clustered at the province level. *, **, *** indicate statistical significance at the 10%, 5%, and 1%, respectively.

Table 3.6: Determinants of Post COVID-19 Financial Constraints

Dependent Variable:	Credit constrained (Post COVID-19)		
	(1)	(2)	(3)
Deaths	0.0210	0.0206	0.0202
	[0.0182]	[0.0192]	[0.0198]
Essential	-0.0000649	0.00376	0.00881
	[0.0450]	[0.0437]	[0.0408]
Liquidity	-0.433***	-0.353***	-0.303***
	[0.0979]	[0.0890]	[0.0938]
Cash Flow	-0.151***	-0.152***	-0.143***
	[0.0332]	[0.0310]	[0.0290]
Leverage	0.00164*	0.00142	0.00172**
	[0.000916]	[0.000864]	[0.000789]
Trade Credit	-0.213*	-0.200*	-0.245**
	[0.112]	[0.111]	[0.109]
Tangible Assets	-0.0770	-0.0690	-0.0930
	[0.0854]	[0.0881]	[0.0872]
Size	-0.0225	-0.0154	-0.0265
	[0.0153]	[0.0146]	[0.0171]
Age	0.0227	0.0202	0.0221
	[0.0254]	[0.0249]	[0.0228]
Group	-0.0721	-0.0803	-0.0809
	[0.0565]	[0.0526]	[0.0521]
Credit constrained		0.171***	0.198***
		[0.0535]	[0.0562]
N of Lender Banks			0.105*
			[0.0539]
Lending Relationship (Years)			-0.0199
			[0.0275]
Distance with lender bank			0.000422
			[0.0169]
Region FE	✓	✓	✓
Industry (2 Digit) FE	✓	✓	✓
Lender Bank FE	X	X	✓
Wide controls	✓	✓	✓
Pseudo R-squared	0.144	0.170	0.182
N obs.	4693	4693	4613

Notes: The dependent variable is a dummy variable representing whether or not the firm is financially constrained. Logit marginal effects for weighted sample. Standard error (in square brackets) clustered at the province level. *, **, *** indicate statistical significance at the 10%, 5%, and 1%, respectively.

Table 3.7: Model with Interactions for Expected Sales Growth

Model	OLS		Ordered Logit		
Dependent variable:	$\mathbb{E}_{i,t}(\text{Sales}^g 1\text{Y})$	$\mathbb{E}_{i,t}(\text{Sales}^g 1\text{Y})$	$\mathbb{E}_{i,t}(\text{Sales}^g 1\text{Y})$	$\mathbb{E}_{i,t}(\text{Sales}^g 1\text{Y})$	$\Delta^R\mathbb{E}_{i,t}(\text{Sales}^g 1\text{Y})$
	(1)	(2)	(3)	(4)	(5)
Deaths	-0.0587***	-0.0552**	-0.144**	-0.138**	-0.146**
	[0.0219]	[0.0214]	[0.0694]	[0.0703]	[0.0681]
Essential	0.385***	0.374***	1.041***	1.023***	1.050***
	[0.0581]	[0.0617]	[0.163]	[0.175]	[0.170]
Credit constrained	-0.347***	-0.327***	-1.448***	-1.391***	-0.956***
	[0.0922]	[0.0891]	[0.343]	[0.332]	[0.226]
Constrained × Deaths	0.0818	0.0663	0.209	0.154	0.195
	[0.0600]	[0.0556]	[0.211]	[0.211]	[0.177]
Constrained × Essential	0.155	0.153	0.925**	0.906**	0.434
	[0.143]	[0.140]	[0.442]	[0.441]	[0.382]
Region FE	✓	✓	✓	✓	✓
Industry (2 Digit) FE	✓	✓	✓	✓	✓
Wide Controls	X	✓	X	✓	✓
R-squared (Pseudo R2)	0.259	0.272	(0.147)	(0.155)	(0.245)
N obs.	5008	5008	5008	5008	5008

Notes: Weighted OLS and ordered logistic estimates. Standard error (in square brackets) clustered at the province level. *, **, *** indicate statistical significance at the 10%, 5%, and 1%, respectively.

Table 3.8: Model with Interactions for Expected Price Growth

Dependent variable:	$\mathbb{E}_{i,t}(\mathrm{P}^g)$	$\mathbb{E}_{i,t}(\mathrm{P}^g)$	$\Delta^R\mathbb{E}_{i,t}(\mathrm{P}^g)$
	(1)	(2)	(3)
Deaths	2.701***	2.518***	2.600***
	[0.957]	[0.863]	[0.847]
Essential	-0.980	-1.390	-1.727
	[2.677]	[2.456]	[2.579]
Credit constrained	11.27**	10.37**	9.832*
	[4.662]	[4.861]	[5.297]
Constrained × Deaths	-0.718	-0.109	2.020
	[1.693]	[1.625]	[1.512]
Constrained × Essential	-9.835**	-9.204**	-9.381*
	[4.002]	[4.070]	[4.889]
$\mathbb{E}_{i,t-1}(\mathrm{P}^g)$	0.121	0.138	
	[0.0835]	[0.0893]	
Region FE	✓	✓	✓
Industry (2 Digit) FE	✓	✓	✓
Wide Controls	X	✓	✓
R-squared	0.192	0.202	0.216
N obs.	4886	4886	4886

Notes: Weighted OLS estimates. Standard error (in square brackets) clustered at the province level. *, **, *** indicate statistical significance at the 10%, 5%, and 1%, respectively.

Table 3.9: Model with Interactions for Continuous Measures for Sales, Orders, Employment, and Investment

	(1)	(2)	(3)	(4)	(5)	(6)
	$\mathbb{E}_{i,t}(\text{Sal}^g\text{3M})$	$\mathbb{E}_{i,t}(\text{Sal}^g\text{1Y})$	$\mathbb{E}_{i,t}(\text{Ord}^g)$	$\mathbb{E}_{i,t}(\text{Emp}^g)$	$\mathbb{E}_{i,t}(\text{Tan}^g)$	$\mathbb{E}_{i,t}(\text{Int}^g)$
Deaths	-0.581	-1.744***	-1.765***	-1.448*	-1.727	-0.227
	[0.573]	[0.544]	[0.581]	[0.809]	[1.147]	[0.696]
Essential	9.459***	7.895***	5.815***	5.345***	8.505***	6.908***
	[1.765]	[1.613]	[1.754]	[1.737]	[3.053]	[2.454]
Credit constrained	-10.67*	-12.10***	-12.80**	-3.471	-13.96**	-12.75**
	[5.424]	[4.447]	[4.972]	[3.947]	[6.428]	[5.712]
Constrained $\times$ Deaths	-8.954***	0.240	-1.148	-1.056	1.593	0.00685
	[2.987]	[1.981]	[2.268]	[2.850]	[2.761]	[2.292]
Constrained $\times$ Essential	5.227	7.092	6.211	-6.153	13.67**	12.60**
	[6.856]	[5.389]	[5.862]	[5.386]	[5.530]	[5.272]
Region FE	✓	✓	✓	✓	✓	✓
Industry (2 Digit) FE	✓	✓	✓	✓	✓	✓
Wide Controls	✓	✓	✓	✓	✓	✓
R-squared	0.333	0.312	0.275	0.265	0.206	0.203
N obs.	5008	5007	5007	5007	5004	5003

Notes: Weighted OLS estimates. Standard error (in square brackets) clustered at the province level. *, **, *** indicate statistical significance at the 10%, 5%, and 1%, respectively.

Table 3.10: Model with Additional Interactions for Expected Price Growth

Dependent variable:	$\mathbb{E}_{i,t}(\mathrm{P}^g)$	$\mathbb{E}_{i,t}(\mathrm{P}^g)$	$\Delta^R\mathbb{E}_{i,t}(\mathrm{P}^g)$
	(1)	(2)	(3)
Deaths	2.698***	2.514***	2.595***
	[0.963]	[0.870]	[0.853]
Essential	-0.850	-1.288	-1.617
	[2.699]	[2.464]	[2.583]
Credit constrained	-2.085	-3.848	-6.606
	[5.201]	[5.198]	[6.670]
Constrained × Deaths	-1.521	-0.880	1.461
	[1.647]	[1.608]	[1.578]
Constrained × Essential	-10.82**	-9.944**	-9.999*
	[4.209]	[4.383]	[5.429]
Constrained × Concentration	3.483***	3.347***	3.033**
	[0.991]	[1.061]	[1.165]
Constrained × Churning	3.787**	4.080**	4.772**
	[1.714]	[1.821]	[1.957]
$\mathbb{E}_{i,t-1}(\mathrm{P}^g)$	0.122	0.139	
	[0.0824]	[0.0871]	
Region FE	✓	✓	✓
Industry (2 Digit) FE	✓	✓	✓
Wide Controls	✓	✓	✓
R-squared	0.202	0.213	0.226
N obs.	4877	4877	4877

Notes: Weighted OLS estimates. Standard error (in square brackets) clustered at the province level. *, **, *** indicate statistical significance at the 10%, 5%, and 1%, respectively.

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Appendix A

Financial and Uncertainty Shocks

A.1 Firm-level evidence

A.1.1 Supportive evidence

I now provide reduced-form cross-sectional evidence that supports the empirical relevance of Proposition 1.1. Using Compustat data, I document how firms' cash management is differently affected by changes in firm-specific credit conditions and changes in firm-specific uncertainty. Firm-specific credit conditions are proxied by the Interest Rate$_{i,t}$ measured as the total interest and related expenses over total liabilities. This ratio is an average interest rate paid by firm i at time t and is aimed to capture possible changes in the cost of external finance. Firm-specific Uncertainty$_{i,t}$ is defined as the standard deviation of income before extraordinary items over the past 16 quarters. As suggested by Han and Qiu (2007), this measure is aimed to capture future expected cash flow risk at a firm level.

With those two measures in hand, the objective is to estimate their relation with firm-level corporate $\text{Cash}_{i,t}$ holdings measured as cash and short-term investments over total assets. I estimate the following regression,

$$\text{Cash}_{i,t} = \alpha + \beta_f \text{Interest Rate}_{i,t} + \beta_u \text{Uncertainty}_{i,t} + \gamma_W W_{i,t} + \lambda_i + \lambda_t + \epsilon_{i,t}$$

where $W_{i,t}$ is a vector of controls that contains the lagged values of $\text{Cash}_{i,t-1}$ and the log of total $\text{Assets}_{i,t-1}$. $W_{i,t}$ also contains the log of Long-Term $\text{Debt}_{i,t}$ and the Long-Term Debt $\text{Ratio}_{i,t}$ (Long-Term $\text{Debt}_{i,t}$ over $\text{Assets}_{i,t}$) to control for changes in the duration of firm i's liabilities, and $\text{Income}_{i,t}$ before extraordinary items to control for idiosyncratic first-moment real shocks. Finally, I also control for λ_i and λ_t which represent firm fixed effects and time fixed effects, respectively. Residual $\epsilon_{i,t}$ is a firm-level time-varying innovation assumed to be uncorrelated with Interest $\text{Rate}_{i,t}$ and $\text{Uncertainty}_{i,t}$. See Appendix A.1 for details on data sources and construction.

The hypothesis to be tested is whether the sign of β_f is significantly negative and the sign of β_u is significantly positive. Baseline results are presented in Table A.1. The table shows strong evidence favoring the mechanism that a worsening in credit conditions — a rise in Interest $\text{Rate}_{i,t}$ — is associated with a fall in corporate $\text{Cash}_{i,t}$ holdings, while an increase in risk — a rise in $\text{Uncertainty}_{i,t}$ — is related to an increase in corporate $\text{Cash}_{i,t}$. Results are robust using different sets of controls and including utility and financial firms in the sample.

Table A.1: Firm-level evidence

VARIABLES	(1) $\text{Cash}_{i,t}$	(2) $\text{Cash}_{i,t}$	(3) $\text{Cash}_{i,t}$	(4) $\text{Cash}_{i,t}$	(5) $\text{Cash}_{i,t}$	(6) $\text{Cash}_{i,t}$
Interest $\text{Rate}_{i,t}$	-0.452***	-0.182***	-0.208***	-0.187***	-0.179***	-0.167***
	(0.0440)	(0.0517)	(0.0605)	(0.0611)	(0.0556)	(0.0539)
$\text{Uncertainty}_{i,t}$	0.0152***	0.0150***	0.0156***	0.0131***	0.0164***	0.0206***
	(0.00388)	(0.00388)	(0.00388)	(0.00381)	(0.00354)	(0.00336)
$\text{Cash}_{i,t-1}$	0.847***	0.844***	0.844***	0.844***	0.845***	0.848***
	(0.00422)	(0.00431)	(0.00432)	(0.00432)	(0.00396)	(0.00383)
$\text{Assets}_{i,t-1}$	-0.0763***	0.148***	0.162***	0.150***	0.0725**	0.0770**
	(0.0152)	(0.0343)	(0.0428)	(0.0435)	(0.0370)	(0.0363)
Long-Term $\text{Debt}_{i,t}$		-0.189***	-0.206***	-0.212***	-0.155***	-0.189***
		(0.0242)	(0.0354)	(0.0353)	(0.0304)	(0.0300)
Long-term debt $\text{ratio}_{i,t}$			0.156	0.206	-0.195	0.0465
			(0.185)	(0.184)	(0.132)	(0.128)
$\text{Income}_{i,t}$				0.0123***	0.0117***	0.0119***
				(0.00324)	(0.00294)	(0.00269)
Firm fixed effects λ_i	✓	✓	✓	✓	✓	✓
Quarter fixed effects λ_t	✓	✓	✓	✓	✓	✓
Utility firms	✗	✗	✗	✗	✓	✓
Financial firms	✗	✗	✗	✗	✗	✓
Observations	62,014	62,014	62,014	62,014	75,213	82,725
Adj. R-squared	0.801	0.802	0.802	0.802	0.803	0.810

Notes. OLS estimates with robust standard errors.

A.1.2 Data sources and other details

- Software: `Stata 15.1 SE`

- Data from Compustat (Wharton Reseach Data Service via Boston College affiliation) at a quarterly frequency. Data range 2004:Q1-2018Q4.

- Keep final reports, remove double observations and observations where total assets (atq), cash (chq), cash and short-term investment (cheq), interest rate expenses (xintq), long-term debt (dlttq), or total liabilities (ltq) are non-positive or missing.

- Define corporate cash holdings over total assets Cash$_{i,t}$ as cash and short-term investments (cheq) over total assets (atq) of firm i at time t. Definition is from the literature.

- Define Interest rate$_{i,t}$ as total interest and related expense (xintq) over total liabilities (ltq) of firm i at time t.

- Define Uncertainty$_{i,t}$ as the standard deviation of income before extraordinary items (ibq) over the past four years (16 quarters) of firm i at time t over 1000 (Han and Qiu, 2007).

- Define Assets$_{i,t}$ as the log of total assets (atq) over 100; Long-Term Debt$_{i,t}$ as the log of long-term debt (dlttq) over 100; Long-Term Debt Ratio$_{i,t}$ as long-term debt (dlttq) over total liabilities (ltq) over 100; Income$_{i,t}$ as income before extraordinary items (ibq) over 1000.

- Run a series of distinct panel regressions with firm and time fixed effects to detect outliers from the residuals of Cash$_{i,t}$, Interest rate$_{i,t}$, Uncertainty$_{i,t}$, Assets$_{i,t}$, Long-Term Debt$_{i,t}$, Long-Term Debt Ratio$_{i,t}$, and Income$_{i,t}$, cash and short-term investment (cheq), and total liabilities (ltq). Remove observations if the related residuals on at least one regression is below the 5th percentile or above the 95th percentile.

- At this point, 62,014 observations are left.

- Run the regressions presented in Section A.1.1 using the package `reghdfe` with robust standard errors.

A.1.3 Comparison with existing firm-level evidence

Results presented above are consistent with a large set of existing firm-level evidence that studies the relation between corporate cash with financial conditions or uncertainty.

In the case of financial conditions, Keynes (1973) argued that the relevance of holding cash is influenced by the extent to which firms have access to external capital markets: if firms are financially constrained, a more liquid balance sheet allows firms to undertake valuable projects when they arise. For example, Campello et al. (2010) gather firm-level information using a survey of 1050 CFOs in the forth quarter of 2008. Their approach provides the opportunity to directly ask managers whether their decisions have been affected by the cost or availability of credit. They find that firms that report themselves as being financially constrained systematically planned to store less cash in order to use it as an internally generated source of finance. Specifically, corporate cash in those firms significantly decrease by 3% while cash holdings in unconstrained firms remain unchanged. In addition, Lins et al. (2010) use a 2005 survey of CFOs and ask whether firms opt for storing additional non-operational cash. Among a different set of answers, CFOs state that cash reserves act as a buffer against future cash flow shortfalls and how much should be stored depends on the interest rates and time needed to rise funds. Finally, Lins et al. (2010) also show that non-operational aggregate cash holdings are positively related to private credit-to-GDP, suggesting that when aggregate credit constraints are tight firms tend to draw down relatively more cash as a substitute for the lack of external finance.

In the case of uncertainty, existing firm-level evidence suggests that firms hold more cash in response to higher cash flow risks due to a precautionary motive. For example, the empirical evidence by Opler et al. (1999) suggests that firms tend to hold more liquid assets if their industry average cash flow volatility is higher. Analogously to the results presented in Table A.1, Han and Qiu (2007), among others, show that higher cash flow volatility is associated with an increase in the stock of corporate cash holdings. Moreover, the empirical evidence presented by Bates et al. (2009) suggests that the medium-run increase in cash ratios can largely be explained by the change in firms' characteristics. In particular, the evidence is consistent with the view that the precautionary motive is a key determinant of the demand for cash. Finally, Alfaro et al. (2018) use U.S. firm-level data to show that firms accumulate cash reserves and short-term liquid instruments following an uncertainty hike.

I interpret those results, together with the partial equilibrium model presented in Section 1.2.1, as as robust support for my identifying assumption. In addition, in Section 2.3, I will embed the partial equilibrium model in a New Keynesian framework and show that the intuition and results are robust after controlling for general equilibrium forces.

A.2 Proof of Proposition 2

Proof. Consider C as the Cholesky decomposition of Σ,

$$CC' = \begin{pmatrix} c_{1,1} & 0 & 0 \\ c_{2,1} & c_{2,2} & 0 \\ c_{3,1} & c_{3,2} & c_{3,3} \end{pmatrix} \begin{pmatrix} c_{1,1} & c_{2,1} & c_{3,1} \\ 0 & c_{2,2} & c_{3,2} \\ 0 & 0 & c_{3,3} \end{pmatrix} = \begin{pmatrix} \sigma_f^2 & \sigma_{f,u} & \sigma_{f,x} \\ \sigma_{f,u} & \sigma_u^2 & \sigma_{u,x} \\ \sigma_{f,x} & \sigma_{u,x} & \sigma_x^2 \end{pmatrix} = \Sigma,$$

where $\sigma_{i,j}^2$ represents the covariance between variable i and variable j. After eliminating the superfluous equations, solution of the system is

$$\begin{cases} c_{1,1}^2 = \sigma_f^2 \\ c_{1,1}c_{2,1} = \sigma_{f,u} \\ c_{1,1}c_{3,1} = \sigma_{f,x} \\ c_{2,1}^2 + c_{2,2}^2 = \sigma_u^2 \\ c_{2,1}c_{3,1} + c_{2,2}c_{3,2} = \sigma_{u,x} \\ c_{3,1}^2 + c_{3,2}^2 + c_{3,3}^2 = \sigma_x^2 \end{cases} \Rightarrow \begin{cases} c_{1,1} = \sigma_f \\ c_{2,1} = \frac{\sigma_{f,u}}{\sigma_f} \\ c_{3,1} = \frac{\sigma_{f,x}}{\sigma_f} \\ c_{2,2} = \sqrt{\sigma_u^2 - (\frac{\sigma_{f,u}}{\sigma_f})^2} \\ c_{3,2} = \frac{\sigma_{u,x} - \frac{\sigma_{f,u}\sigma_{f,x}}{\sigma_f^2}}{\sqrt{\sigma_u^2 - (\frac{\sigma_{f,u}}{\sigma_f})^2}} \\ c_{3,3} = \sqrt{\sigma_x^2 - (\frac{\sigma_{f,x}}{\sigma_f})^2 - \frac{(\sigma_{u,x} - \frac{\sigma_{f,u}\sigma_{f,x}}{\sigma_f^2})^2}{\sigma_u^2 - (\frac{\sigma_{f,u}}{\sigma_f})^2}}. \end{cases}$$

Define orthogonal matrix D as follows

$$D = \begin{pmatrix} d_1, & d_2, & d_3 \end{pmatrix} = \begin{pmatrix} \gamma_{1,1} & \gamma_{1,2} & \gamma_{1,3} \\ \gamma_{2,1} & \gamma_{2,2} & \gamma_{2,3} \\ \gamma_{3,1} & \gamma_{3,2} & \gamma_{3,3} \end{pmatrix}$$

then $A = CD$ can be rewritten as,

$$A = \begin{pmatrix} c_{1,1}\gamma_{1,1} & c_{1,1}\gamma_{1,2} & \cdots \\ c_{2,1}\gamma_{1,1} + c_{2,2}\gamma_{2,1} & c_{2,1}\gamma_{1,2} + c_{2,2}\gamma_{2,2} & \cdots \\ c_{3,1}\gamma_{1,1} + c_{3,2}\gamma_{2,1} + c_{3,3}\gamma_{3,1} & c_{3,1}\gamma_{1,2} + c_{3,2}\gamma_{2,2} + c_{3,3}\gamma_{3,2} & \cdots \end{pmatrix} \tag{A.1}$$

where the first column represents the impact effect of the first and second shock on financial conditions f_t, measured uncertainty u_t, and the cash holdings x_t^f, respectively. The third column, which represents the impact responses of the endogenous variables to other shocks, is omitted because, as discussed above, independent to the identification of financial and uncertainty shocks.

Then, Problems 1.3 and 1.4 can be rewritten as follows

$$\begin{aligned} \max_{\gamma_{1,1},\gamma_{2,1},\gamma_{3,1}} \quad & (1-\delta)c_{1,1}\gamma_{1,1} - \delta[c_{3,1}\gamma_{1,1} + c_{3,2}\gamma_{2,1} + c_{3,3}\gamma_{3,1}] \\ \text{subject to} \quad & (\gamma_{1,1})^2 + (\gamma_{2,1})^2 + (\gamma_{3,1})^2 = 1 \end{aligned}$$

and

$$\begin{aligned} \max_{\gamma_{1,2},\gamma_{2,2},\gamma_{3,2}} \quad & (1-\delta)[c_{2,1}\gamma_{1,2} + c_{2,2}\gamma_{2,2}] + \delta[c_{3,1}\gamma_{1,2} + c_{3,2}\gamma_{2,2} + c_{3,3}\gamma_{3,2}] \\ \text{subject to} \quad & (\gamma_{1,2})^2 + (\gamma_{2,2})^2 + (\gamma_{3,2})^2 = 1. \end{aligned}$$

where $d_1^*(\delta)$ and $d_2^*(\delta)$ are the respective solutions for financial and uncertainty shocks that, for a given δ, are uniquely identified.

The first order conditions of Problem 1.3 are:

i. $\gamma_{1,1}: \; (1-\delta)c_{1,1} - \delta c_{3,1} = 2\lambda\gamma_{1,1}^*$

ii. $\gamma_{2,1}: \ -\delta c_{3,2} = 2\lambda\gamma^*_{2,1}$

iii. $\gamma_{3,1}: \ -\delta c_{3,3} = 2\lambda\gamma^*_{3,1}$

iv. $\lambda_1: \ (\gamma^*_{1,1})^2 + (\gamma^*_{2,1})^2 + (\gamma^*_{3,1})^2 = 1$

where λ_1 is the Lagrangian multiplier of the constraint.

If $\delta = 0$, solution is $\gamma^*_{1,1} = 1$ and $\gamma^*_{2,1} = \gamma^*_{3,1} = 0$ where the impact effect on financial conditions f_t is σ_f which is the result of a Cholesky identification where f_t is placed on top. As a result, if $\delta = 0$ then $\varepsilon^f_t = i^f_t$. Conversely, if $\delta = 1$, solution is

$$\begin{cases} \gamma^*_{1,1} = -\sqrt{\frac{c^2_{3,1}}{c^2_{3,1}+c^2_{3,2}+c^2_{3,2}}} \\ \gamma^*_{2,1} = -\sqrt{\frac{c^2_{3,2}}{c^2_{3,1}+c^2_{3,2}+c^2_{3,2}}} \\ \gamma^*_{3,1} = -\sqrt{\frac{c^2_{3,3}}{c^2_{3,1}+c^2_{3,2}+c^2_{3,2}}} \end{cases}$$

which delivers an impact effect on corporate cash x^f_t of $-\sigma_x$. As a result, if $\delta = 1$ then $\varepsilon^u_t = -i^x_t$ which is the result of a Cholesky identification where x^f_t is placed on top with opposite sign.

The first order conditions of Problem 1.4 are:

i. $\gamma_{1,2}: \ (1-\delta)c_{2,1} + \delta c_{3,1} = 2\lambda\gamma^*_{1,2}$

ii. $\gamma_{2,2}: \ (1-\delta)c_{2,2} + \delta c_{3,2} = 2\lambda\gamma^*_{2,2}$

iii. $\gamma_{3,2}: \ \delta c_{3,3} = 2\lambda\gamma^*_{3,2}$

iv. $\lambda_2: \ (\gamma^*_{1,2})^2 + (\gamma^*_{2,2})^2 + (\gamma^*_{3,2})^2 = 1$

where λ_2 is the Lagrangian multiplier of the constraint.

If $\delta = 0$, solution is

$$\begin{cases} \gamma^*_{1,2} = \sqrt{\frac{c^2_{3,1}}{c^2_{2,1}+c^2_{2,2}}} \\ \gamma^*_{2,2} = \sqrt{\frac{c^2_{2,2}}{c^2_{2,1}+c^2_{2,2}}} \\ \gamma^*_{3,2} = 0 \end{cases}$$

where the impact effect on measured uncertainty u_t is σ_u which is the result of a Cholesky identification where u_t is placed on top. As a result, if $\delta = 0$ then $\varepsilon^u_t = i^u_t$. Conversely, if $\delta = 1$, solution is

$$\begin{cases} \gamma^*_{1,1} = \sqrt{\frac{c^2_{3,1}}{c^2_{3,1}+c^2_{3,2}+c^2_{3,2}}} \\ \gamma^*_{2,1} = \sqrt{\frac{c^2_{3,2}}{c^2_{3,1}+c^2_{3,2}+c^2_{3,2}}} \\ \gamma^*_{3,1} = \sqrt{\frac{c^2_{3,3}}{c^2_{3,1}+c^2_{3,2}+c^2_{3,2}}} \end{cases}$$

which delivers an impact effect on the liquidity ration x^f_t of σ_x. As a result, if $\delta = 1$ then $\varepsilon^u_t = i^x_t$ which is the result of a Cholesky identification where x^f_t is placed on top.

Now if $\delta = 0$, then $d^*_1(\delta = 0)' d^*_2(\delta = 0) = \text{Corr}(\varepsilon^f_t, \varepsilon^u_t) = \text{Corr}(i^f_t, i^u_t) > 0$. While, if $\delta = 1$, then $d^*_1(\delta = 1)' d^*_2(\delta = 1) = \text{Corr}(\varepsilon^u_t, \varepsilon^f_t) = \text{Corr}(i^x_t, -i^x_t) = -1$. Since both $d^*_1(\delta)$ and $d^*_2(\delta)$ are continuous functional vectors in δ, it follows that also their product $d^*_1(\delta)' d^*_2(\delta)$ is continuous in δ. This implies that $d^*_1(\delta)' d^*_2(\delta)$ must cross the zero line at least once in the δ support $[0, 1]$.

$\blacksquare$

A.3 Proposition 3

Proposition 3 *If Cov$(i_t^u, i_t^f) = \sigma_u \sigma_f$ then solution δ^*, d_1^*, and d_2^* exists and is unique.*

Proof. Notice that Cov$(i_t^u, i_t^f) = \sigma_u \sigma_f$ directly implies that Corr(i_t^u, i_t^f) is equal to one. This entails that the system is collapsing because the information to identify impact matrix A provided by u_t already includes all the information provided by f_t and viceversa. As a result, I will shrink the system to be bidimensional where the first series of innovations i_t^1 is equal to the innovations in both measured uncertainty i_t^u and financial conditions i_t^f with standard deviation σ_1; while the second series of innovations i_t^2 is equal to the innovations in corporate cash i_t^x with standard deviation σ_x. As before, I am interested in identifying the first two structural disturbances: financial shocks ε_t^F and uncertainty shocks ε_t^U. Identifying assumptions are the same: financial shocks ε_t^F have a positive impact effect on i_t^1 (first variable) and a negative impact effect on i_t^2 (second variable), while uncertainty shocks ε_t^U have a positive impact effect on both reduced-form innovations i_t^1 and i_t^2.

Consider the solution to the Cholesky identification where $c_{1,2} = 0$,

$$C = \begin{pmatrix} \sigma_{1,1} & 0 \\ \frac{\sigma_{1,2}^2}{\sigma_{1,1}} & \sqrt{\sigma_{2,2}^2 - \left(\frac{\sigma_{1,2}^2}{\sigma_{1,1}}\right)^2} \end{pmatrix} = \begin{pmatrix} c_{1,1} & c_{1,2} \\ c_{2,1} & c_{2,2} \end{pmatrix}$$

where, as before, $CC' = \Sigma$. Given orthogonal matrix D, impact matrix A is

$$A = \begin{pmatrix} c_{1,1}\gamma_{1,1} & c_{1,1}\gamma_{1,2} \\ c_{2,1}\gamma_{1,1} + c_{2,2}\gamma_{2,1} & c_{2,1}\gamma_{1,2} + c_{2,2}\gamma_{2,2} \end{pmatrix}$$

which is

$$A = \begin{pmatrix} \sigma_{1,1}\gamma_{1,1} & \sigma_{1,1}\gamma_{1,2} \\ \frac{\sigma_{1,2}^2}{\sigma_{1,1}}\gamma_{1,1} + \sqrt{\sigma_{2,2}^2 - \left(\frac{\sigma_{1,2}^2}{\sigma_{1,1}}\right)^2}\gamma_{2,1} & \frac{\sigma_{1,2}^2}{\sigma_{1,1}}\gamma_{1,2} + \sqrt{\sigma_{2,2}^2 - \left(\frac{\sigma_{1,2}^2}{\sigma_{1,1}}\right)^2}\gamma_{2,2} \end{pmatrix}.$$

Although results remain perfectly symmetric, consider the case where the impact responses to an uncertainty shock are represented by the first column of Matrix A, and the impact responses to a financial shock are represented by the second column of Matrix A. Problem 1.4 – to identify uncertainty shocks – can be rewritten as,

$$\max_{\gamma_{1,1},\gamma_{2,1}} \quad \sigma_{1,1}\gamma_{1,1} + \delta\left[\frac{\sigma_{1,2}^2}{\sigma_{1,1}}\gamma_{1,1} + \sqrt{\sigma_{2,2}^2 - \left(\frac{\sigma_{1,2}^2}{\sigma_{1,1}}\right)^2}\gamma_{2,1}\right]$$
$$\text{s.t.} \quad 1 \geq \gamma_{1,1}^2 + \gamma_{2,1}^2$$

and optimality conditions are

$$\gamma_{1,1}: \ \sigma_{1,1} + \delta\frac{\sigma_{1,2}^2}{\sigma_{1,1}} - 2\lambda\big(\gamma_{1,1}^*\big) = 0 \quad \Rightarrow \quad \gamma_{1,1}^* = \frac{1}{2\lambda}\left[\sigma_{1,1} + \delta\frac{\sigma_{1,2}^2}{\sigma_{1,1}}\right] \tag{A.2}$$

$$\gamma_{2,1}: \ \delta\sqrt{\sigma_{2,2}^2 - \left(\frac{\sigma_{1,2}^2}{\sigma_{1,1}}\right)^2} - 2\lambda\big(\gamma_{2,1}^*\big) = 0 \quad \Rightarrow \quad \gamma_{2,1}^* = \frac{1}{2\lambda}\delta\sqrt{\sigma_{2,2}^2 - \left(\frac{\sigma_{1,2}^2}{\sigma_{1,1}}\right)^2} \tag{A.3}$$

$$\lambda : (\gamma_{1,1}^*)^2 - (\gamma_{2,1}^*)^2 = 1 \tag{A.4}$$

where λ is the Lagrangian multiplier of the constraint. The following results will be useful to complete the proof:

- Equation A.2 implies that

  1. $\gamma^*_{1,1} \geq 0$ for all $\delta \geq 0$ if $\sigma^2_{1,2} \geq 0$.

  2. It exists $\bar{\delta}$ such that $\gamma^*_{1,1} \geq 0$ for all $0 \leq \delta \leq \bar{\delta}$ if $\sigma^2_{1,2} \leq 0$.

- Equation A.3 implies $\gamma^*_{2,1} \geq 0$ for all $\delta \geq 0$.

- Dividing A.2 over A.3 yields

$$\frac{\gamma^*_{1,1}}{\gamma^*_{2,1}} = \frac{\sigma_{1,1} + \delta \frac{\sigma^2_{1,2}}{\sigma_{1,1}}}{\delta \sqrt{\sigma_{2,2} - \left(\frac{\sigma^2_{1,1}}{\sigma_{1,1}}\right)^2}}$$

  Taking first derivative with respect to δ implies

$$\frac{\partial \frac{\gamma^*_{1,1}}{\gamma^*_{2,1}}}{\partial \delta} = \frac{\frac{\sigma^2_{1,2}}{\sigma_{1,1}} \delta \sqrt{\sigma_{2,2} - \left(\frac{\sigma^2_{1,1}}{\sigma_{1,1}}\right)^2} - \left(\sigma_{1,1} + \delta \frac{\sigma^2_{1,2}}{\sigma_{1,1}}\right) \sqrt{\sigma_{2,2} - \left(\frac{\sigma^2_{1,1}}{\sigma_{1,1}}\right)^2}}{\delta^2 \left(\sigma_{2,2} - \left(\frac{\sigma^2_{1,1}}{\sigma_{1,1}}\right)^2\right)}$$

which is

$$\frac{\partial \frac{\gamma^*_{1,1}}{\gamma^*_{2,1}}}{\partial \delta} = -\frac{\sigma_{1,1} \sqrt{\sigma_{2,2} - \left(\frac{\sigma^2_{1,1}}{\sigma_{1,1}}\right)^2}}{\delta^2 \left(\sigma_{2,2} - \left(\frac{\sigma^2_{1,1}}{\sigma_{1,1}}\right)^2\right)} < 0.$$

Problem 1.3 – to identify financial shocks– can be rewritten as,

$$\begin{aligned} \max_{\gamma_{1,2},\gamma_{2,2}} \quad & \sigma_{1,1}\gamma_{1,2} - \delta \left[\frac{\sigma^2_{1,2}}{\sigma_{1,1}} \gamma_{1,2} + \sqrt{\sigma^2_{2,2} - \left(\frac{\sigma^2_{1,2}}{\sigma_{1,1}}\right)^2} \gamma_{2,2} \right] \\ \text{s.t.} \quad & 1 \geq \gamma^2_{1,2} + \gamma^2_{2,2} \end{aligned} \tag{A.5}$$

and optimality conditions are

$$\gamma_{1,2}: \ \sigma_{1,1} - \delta\frac{\sigma_{1,2}^2}{\sigma_{1,1}} - 2\lambda\left(\gamma_{1,2}^*\right) = 0 \ \Rightarrow \ \gamma_{1,2}^* = \frac{1}{2\lambda}\left[\sigma_{1,1} - \delta\frac{\sigma_{1,2}^2}{\sigma_{1,1}}\right] \tag{A.6}$$

$$\gamma_{2,2}: \ -\delta\sqrt{\sigma_{2,2}^2 - \left(\frac{\sigma_{1,2}^2}{\sigma_{1,1}}\right)^2} - 2\lambda\left(\gamma_{2,2}^*\right) = 0 \ \Rightarrow \ \gamma_{2,2}^* = -\frac{1}{2\lambda}\delta\sqrt{\sigma_{2,2}^2 - \left(\frac{\sigma_{1,2}^2}{\sigma_{1,1}}\right)^2} \tag{A.7}$$

$$\lambda := \lambda\left[1 - \left(\gamma_{1,2}^*\right)^2 - \left(\gamma_{2,2}^*\right)^2\right] = 0 \tag{A.8}$$

where λ is the Lagrangian multiplier of the constraint. The following results will be useful to complete the proof:

- Equation A.6 implies that
  1. $\gamma_{1,2}^* \geq 0$ for all $\delta \geq 0$ if $\sigma_{1,2}^2 \leq 0$.
  2. It exists $\bar{\delta}$ such that $\gamma_{1,2}^* \geq 0$ for all $0 \leq \delta \leq \bar{\delta}$ if $\sigma_{1,2}^2 \geq 0$.
- Equation A.7 implies $\gamma_{2,2}^* \leq 0$ for all $\delta \geq 0$.
- Dividing A.6 over A.7 yields

$$\frac{\gamma_{1,2}^*}{\gamma_{2,2}^*} = -\frac{\sigma_{1,1} - \delta\frac{\sigma_{1,2}^2}{\sigma_{1,1}}}{\delta\sqrt{\sigma_{2,2} - \left(\frac{\sigma_{1,1}^2}{\sigma_{1,1}}\right)^2}}$$

Taking first derivative with respect to δ implies

$$\frac{\partial \frac{\gamma^*_{1,2}}{\gamma^*_{2,2}}}{\partial \delta} = -\frac{-\frac{\sigma^2_{1,2}}{\sigma_{1,1}}\delta\sqrt{\sigma_{2,2}-\left(\frac{\sigma^2_{1,1}}{\sigma_{1,1}}\right)^2}-\left(\sigma_{1,1}-\delta\frac{\sigma^2_{1,2}}{\sigma_{1,1}}\right)\sqrt{\sigma_{2,2}-\left(\frac{\sigma^2_{1,1}}{\sigma_{1,1}}\right)^2}}{\delta^2\left(\sigma_{2,2}-\left(\frac{\sigma^2_{1,1}}{\sigma_{1,1}}\right)^2\right)}$$

which is

$$\frac{\partial \frac{\gamma^*_{1,2}}{\gamma^*_{2,2}}}{\partial \delta} = \frac{\sigma_{1,1}\sqrt{\sigma_{2,2}-\left(\frac{\sigma^2_{1,1}}{\sigma_{1,1}}\right)^2}}{\delta^2\left(\sigma_{2,2}-\left(\frac{\sigma^2_{1,1}}{\sigma_{1,1}}\right)^2\right)} > 0$$

Notice that there exist two possible cases to focus on: 1. $\delta \leq \bar{\delta}$ and 2. $\delta > \bar{\delta}$. Proof proceeds as follows: I show that case 1. has a unique solution and case 2. has no solutions. In addition, since the problem is symmetric over d_1 and d_2 is irrelevant whether I focus on $\sigma_{1,2} \geq 0$ or $\sigma_{1,2} \leq 0$. Proof holds symmetrically in either cases. For simplicity I assume $\sigma_{1,2} \geq 0$.

1. When $\delta \leq \bar{\delta}$, at least a solution always exists since for $\delta = 0$,

$$\gamma^*_{1,1}\gamma^*_{1,2} + \gamma^*_{2,1}\gamma^*_{2,2} > 0$$

since $\gamma^*_{1,1} = \gamma^*_{1,2} = 1$, and $\gamma^*_{2,1} = \gamma^*_{2,2} = 0$. Moreover, for $\delta = \bar{\delta}$,

$$\gamma^*_{1,1}\gamma^*_{1,2} + \gamma^*_{2,1}\gamma^*_{2,2} < 0$$

since $\gamma_{1,2} = 0$, $\gamma^*_{2,1} > 0$, and $\gamma^*_{2,2} > 0$.[1]

[1] I am implicitly using the result that $\gamma^*_{1,1}\gamma^*_{1,2} + \gamma^*_{2,1}\gamma^*_{2,2}$ is a continuous function of δ.

Thus, in order to show that the solution is unique, I need to prove that $\gamma^*_{1,1}\gamma^*_{1,2} + \gamma^*_{2,1}\gamma^*_{2,2}$ is monotonically decreasing in δ. Since both $\gamma^*_{1,1}$ and $\gamma^*_{2,1}$ are positive, and since $\frac{\gamma^*_{1,1}}{\gamma^*_{2,1}}$ is decreasing in δ then it must be the case that $\gamma^*_{1,1}$ is decreasing in δ and $\gamma^*_{2,1}$ is increasing in δ. Since $\gamma^*_{1,2}$ is positive and $\gamma^*_{2,2}$ is negative, and since $\frac{\gamma^*_{1,2}}{\gamma^*_{2,2}}$ is increasing in δ then it must be the case that $\gamma^*_{1,2}$ is decreasing in δ and $|\gamma^*_{2,2}|$ is increasing in δ. As a result, we have $(\downarrow \gamma^*_{1,1})(\downarrow \gamma^*_{1,2}) - (\uparrow \gamma^*_{2,1})(\uparrow |\gamma^*_{2,2}|)$ which implies that when $\delta \leq \bar{\delta}$, then $\gamma^*_{1,1}\gamma^*_{1,2} + \gamma^*_{2,1}\gamma^*_{2,2}$ is monotonically decreasing in δ which implies that the solution in this area is unique.

2. When $\delta > \bar{\delta}$, $\gamma^*_{1,1}\gamma^*_{1,2} + \gamma^*_{2,1}\gamma^*_{2,2}$ is never equal to zero. This happens because when $\delta > \bar{\delta}$, $\gamma_{1,1} > 0$, $\gamma_{2,1} > 0$, $\gamma_{1,2} < 0$, and $\gamma_{2,2} < 0$. As a result,

$$\gamma^*_{1,1}\gamma^*_{1,2} + \gamma^*_{2,1}\gamma^*_{2,2} < 0 \ \ \forall \, \delta > \bar{\delta}.$$

■

A.4 Estimation on simulated data

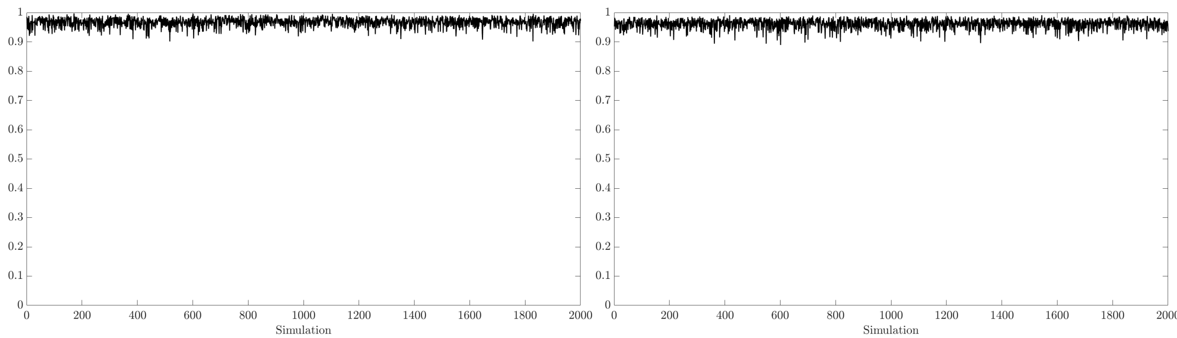
In order to test the reliability of the econometric procedure presented in Section 1.3, I simulate data from the model presented in Section 2.3 and employ my econometric strategy in order to recover unobservable financial and uncertainty shocks from the observable endogenous variables. To be in line with the empirical application presented in Section 1.4, I simulate 2000 series with 137 observations where financial and uncertainty shocks are i.i.d. observations across shocks and over time from a standard normal distribution.[2] I assume the econometrician can only observe endogenous variables such as measured uncertainty u_t, the credit spread as a proxy for financial conditions f_t and the liquidity ratio x_t, and cannot observe exogenous processes such as financial intermediaries' fixed cost χ_t and variance of technology shocks σ_t together with their underlying shocks. Following Jurado et al. (2015), I define measured uncertainty as $u_t = \mathbb{E}_t\{[y_t - \mathbb{E}_t(y_t)]^2\}$. In addition, in order to capture an endogenous variable for financial conditions, I define $f_t = 0.5\bar{a}_t + 0.5\bar{a}_{t+1} + \varphi_t$. Note that both variables display a positive impact effect to financial and uncertainty shocks reproducing the simultaneity observed in the data.

For each simulation, I build a reduced-form VAR composed by measured uncertainty u_t, credit spread f_t, corporate cash x_t^f, output y_t, shadow values ξ_t/ν_t, inflation π_t, total cash $\bar{x}_t$, and policy rate R_t. As suggested by the AIC, BIC and HQ

[2] For simplicity, I do not simulate technology shocks because of the empirical observation that the residuals of the excess bond premium by Gilchrist and Zakrajšek (2012) and of measured uncertainty by Jurado et al. (2015) are already orthogonal to unanticipated technology shocks. In any case, if technology shocks are simulated together with financial and uncertainty shocks, it will be sufficient to control for the residuals in measured productivity before employing the econometric strategy presented in Section 1.3.

Figure A.1: Correlation between actual shocks ε_t and estimated shocks $\hat{\varepsilon}_t$

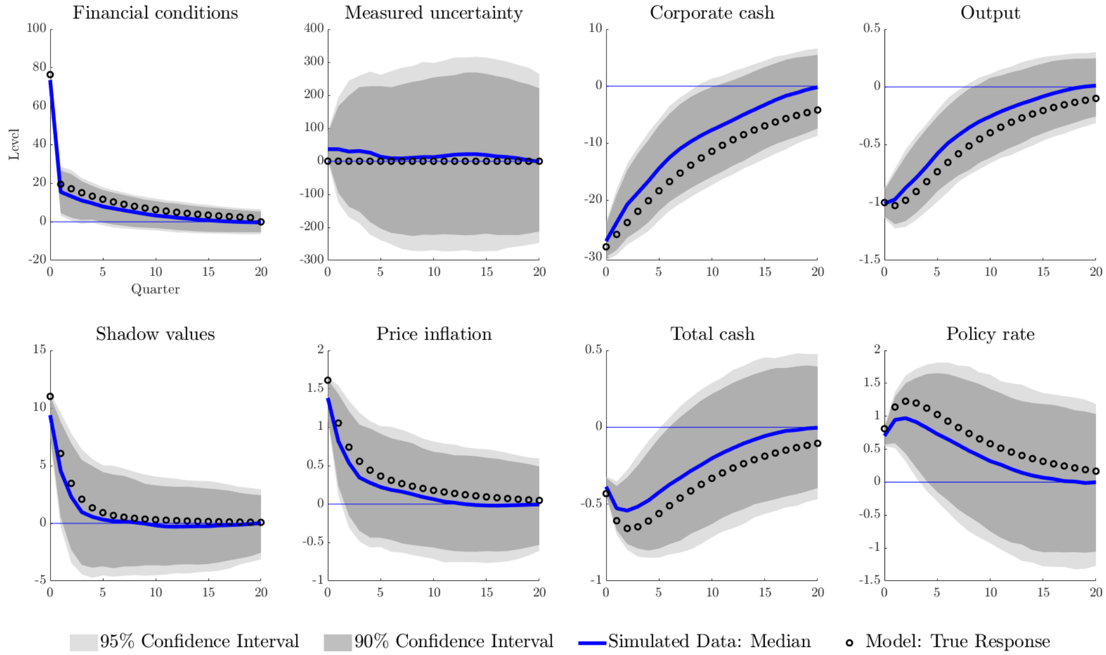
(a) Uncertainty shocks **(b)** Financial shocks



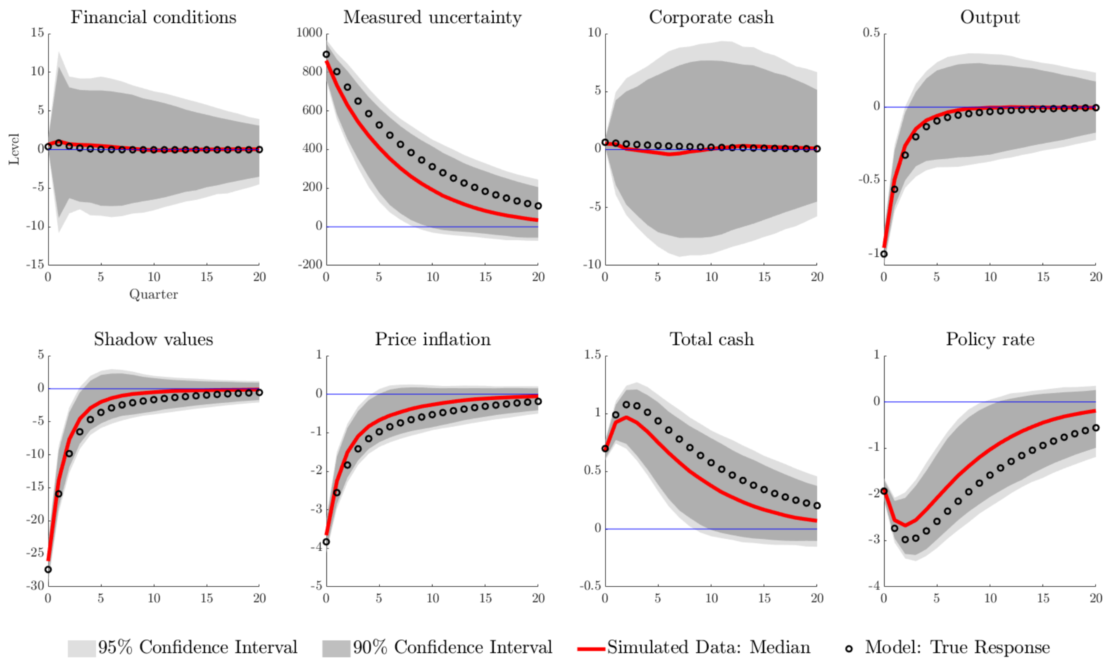
criteria I use one lag to obtain a (8×8) variance-covariance matrix Σ of reduced-form innovations i_t. Finally, making the same assumptions shown in Matrix **??** and remaining agnostic on the response of the remaining macro variables, I employ the same econometric strategy presented in Definition 1. Figure A.1b shows the correlation between actual financial shocks ε_t^F and estimated ones $\hat{\varepsilon}_t^F$ and in most of the cases the correlation is above 90% with an average of 96%. Similarly, Figure A.1a shows the correlation between actual uncertainty shocks ε_t^U and estimated ones $\hat{\varepsilon}_t^U$ and in most of the cases the correlation is above 90% with an average of 96% as well. At the same time, Figure A.2 shows the model-implied true responses together with the estimated ones on simulated data for both financial and uncertainty shocks. The econometric strategy does a good job in estimating the actual responses to the two shocks since, in almost all the cases, the actual responses lie within the confidence interval of the estimated ones.

Figure A.2: Model-implied responses and estimated responses on simulated data

(a) Financial shocks



(b) Uncertainty shocks

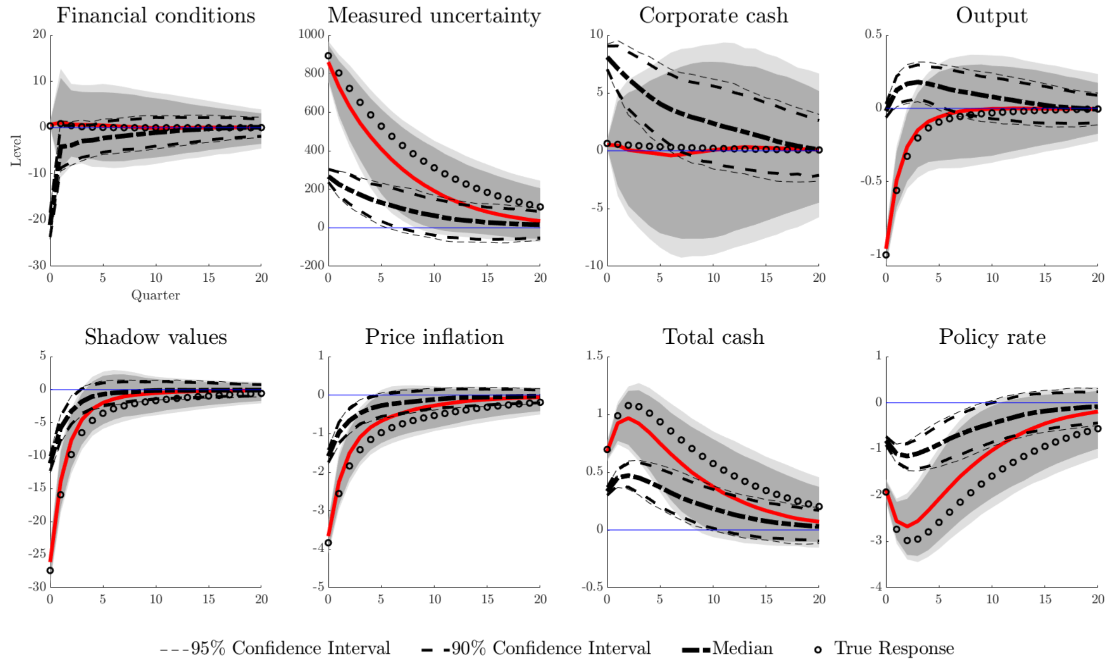


A.5 Comparison with sign restrictions

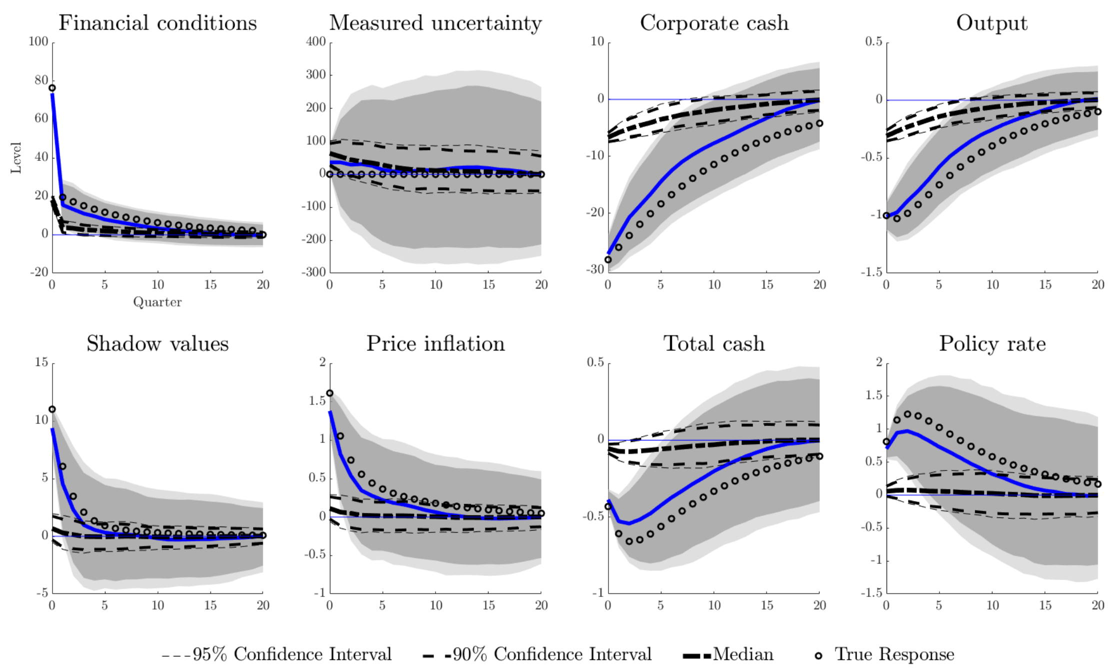
In Figure A.3, I compare the identification strategy presented in Section 1.3 with sign restrictions. Using the same simulated data used to obtain Figure A.2, I implement the following algorithm. For each simulation s, draw C_s using the Cholesky decomposition. Then, draw a random orthogonal matrix Q such that $Q'Q$ is an identity matrix. Generate candidate impact responses from C_sQ and verify if they satisfy the identifying assumptions. If the sign restrictions are not satisfied then disregard Q, if the sign restrictions are satisfied then generate and store its related impulse response functions. Repeat this procedure until N impulse responses are stored and take the simple mean. Repeat this procedure for any simulation s and obtain 2000 mean impulse responses. Derive median and confidence intervals.

Figure A.3: Estimated responses on simulated data: comparison with sign restrictions

(a) Uncertainty shocks



(b) Financial shocks



Note: "B20" stands for Brianti (2020) and refers to the identification strategy presented in Section 1.3. "Sign Restrictions" refers to the sign restriction identification scheme as described in the main text.

A.6 Aggregate data

Table A.2: Details on aggregate US data

Variable	**Source and Construction**	**Transform**
Credit spread: EBP	Excess bond premium by Gilchrist and Zakrajšek (2012) available on Simon Gilchrist's website. Aggregation method: average	level
Measured uncertainty	Macroeconomic uncertainty by Jurado et al. (2015) available on Sydney Ludvigson's website. Baseline specification: horizon is three months. Robustness checks: horizons are one month (MU1) and 12 months (MU12). Aggregation method: average	level
Corporate cash	Sum of (i) private foreign deposits (FDABSNNCB), (ii) checkable deposits and currency (NCBCDCA), (iii) total time and saving deposits (TSDABSNNCB), and (iv) money market mutual fund shares (MMFSABSNNCB); over Total assets (TABSNNCB) by FRED	level
GDP	Real gross domestic product (GDPC1) by FRED	log
Consumption	Consumption of non-durables (RCONND) plus consumption of services (RCONS) by Philadelphia Fed	log
Investment	Gross domestic investment (GDPIC1) by FRED plus consumption of durables (RCOND) by Philadelphia Fed	log
Hours	Hours of all persons for the nonfarm business sector (HOANBS) by FRED	log
GDP deflator	Implicit price deflator of the gross domestic product (GDPDEF) by FRED	log
Real M2	M2 money stock (M2) over GDP deflator (GDPDEF) by FRED	log
FFR	Effective federal funds rate (FEDFUNDS) by FRED	level
Volatility Index (VIX)	Volatility Index VIX (VIXCLS) by FRED. Aggregation method: average	log
Credit spread: GZ	GZ credit spread by Gilchrist and Zakrajšek (2012) available on Simon Gilchrist's website. Aggregation method: average	level
Credit spread: BAA10Y	Moody's Seasoned Baa Corporate Bond Yield Relative to Yield on 10-Year Treasury Constant Maturity, Percent, Quarterly, Not Seasonally Adjusted (BAA10Y) by FRED. Aggregation method: average	level
Measured uncertainty: FU3	Financial uncertainty by Jurado et al. (2015) available on Sydney Ludvigson's website. Horizon is three months. Aggregation method: average	level
Measured uncertainty: RU3	Real uncertainty by Jurado et al. (2015) available on Sydney Ludvigson's website. Horizon is three months. Aggregation method: average	level
Treasury	Treasury (TSABSNNCB) for the nonfinancial corporate business sector by FRED. Robustness check: add it to baseline corporate liquidity	level

A.7 Model's derivations and details

A.7.1 Household cost minimization problem

Household cost minimization problem is:

$$\min_{c_{i,t}} \int_0^1 P_{i,t} c_{i,t} di \qquad \text{subject to:} \quad q_t = \left[\int_0^1 \left(\frac{c_{i,t}}{s^{\theta}_{i,t-1}} \right)^{1-\frac{1}{\eta}} \right]^{\frac{1}{1-\frac{1}{\eta}}}$$

Set up the Lagrangian

$$L = \int_0^1 P_{i,t} c_{i,t} di + \tilde{\psi}_t \left\{ q_t - \left[\int_0^1 \left(\frac{c_{i,t}}{s^{\theta}_{i,t-1}} \right)^{1-\frac{1}{\eta}} \right]^{\frac{1}{1-\frac{1}{\eta}}} \right\}$$

FOC for $c_{i,t}$ is:

$$P_{i,t} = \tilde{\psi}_t \left[\int_0^1 \left(\frac{c_{i,t}}{s^{\theta}_{i,t-1}} \right)^{1-\frac{1}{\eta}} \right]^{\frac{1}{1-\frac{1}{\eta}}-1} \left(\frac{c_{i,t}}{s^{\theta}_{i,t-1}} \right)^{-\frac{1}{\eta}} s^{-\theta}_{i,t-1}$$

which is

$$\left(\frac{c_{i,t}}{s^{\theta}_{i,t-1}} \right)^{\frac{1}{\eta}} = \frac{\tilde{\psi}_t}{P_{i,t}} \left[\int_0^1 \left(\frac{c_{i,t}}{s^{\theta}_{i,t-1}} \right)^{1-\frac{1}{\eta}} \right]^{\frac{1}{1-\frac{1}{\eta}}-1} s^{-\theta}_{i,t-1}$$

which is the good-specific demand in function $\tilde{\psi}_t$:

$$c_{i,t} = \left(\frac{P_{i,t}}{\tilde{\psi}_t} \right)^{-\eta} s^{\theta(1-\eta)}_{i,t-1} q_t$$

Now substitute this equation into the definition for q_t:

$$q_t = \left[\int_0^1 \left(P_{i,t}^{-\eta} \ \psi_t^{\eta} \ s_{i,t-1}^{\theta(1-\eta)} \ q_t \right)^{\frac{\eta-1}{\eta}} \ s_{i,t-1}^{\frac{\theta(1-\eta)}{\eta}} \ di \right]^{\frac{\eta}{\eta-1}}$$

which is

$$\tilde{\psi}_t = \left[\int_0^1 \left(P_{i,t}^{-\eta} \ s_{i,t-1}^{\theta(1-\eta)} \right)^{\frac{\eta-1}{\eta}} \ s_{i,t-1}^{\frac{\theta(1-\eta)}{\eta}} \ di \right]^{\frac{1}{1-\eta}}$$

which delivers

$$\tilde{\psi}_t = \left[\int_0^1 (\ P_{i,t} \ s_{i,t-1}^{\theta} \ )^{1-\eta} \ di \right]^{\frac{1}{1-\eta}}$$

Define $p_{i,t} = P_{i,t}/P_t$ as the variety i price $P_{i,t}$ in terms of the price index $P_t = [\int_0^1 P_{i,t}^{1-\eta} di]^{\frac{1}{1-\eta}}$. This yields

$$\tilde{\psi}_t = \left[\int_0^1 (\ p_{i,t} \ s_{i,t-1}^{\theta} \ )^{1-\eta} \ di \right]^{\frac{1}{1-\eta}} P_t$$

where

$$\frac{\tilde{\psi}_t}{P_t} = \left[\int_0^1 (\ p_{i,t} \ s_{i,t-1}^{\theta} \ )^{1-\eta} \ di \right]^{\frac{1}{1-\eta}} \equiv \tilde{p}_t$$

This implies that

$$c_{i,t} = \left(\frac{P_{i,t}}{\tilde{\psi}_t} \right)^{-\eta} s_{i,t-1}^{\theta(1-\eta)} q_t = \left(\frac{P_{i,t}/P_t}{\tilde{\psi}_t/P_t} \right)^{-\eta} s_{i,t-1}^{\theta(1-\eta)} q_t = \left(\frac{p_{i,t}}{\tilde{p}_t} \right)^{-\eta} s_{i,t-1}^{\theta(1-\eta)} q_t$$

A.7.2 Household utility maximization problem

Household maximization problem is:

$$\max_{q_t,n_t,b_t} \mathbb{E}_t \sum_{s=0}^{\infty} \beta^s \left[\frac{(q_{t+s})^{1-\gamma_q}}{1-\gamma_q} + \chi_n \log(1-n_{t+s}) + \chi_x \log\left(\frac{X_{t+s-1}}{P_t}\right) \right]; \quad 0<\beta<1$$

subject to

$$\tilde{p}_t q_t + \frac{B_t}{P_t} + \frac{X_t^h}{P_t} = w_t n_t + R_{t-1}\frac{B_{t-1}}{P_t} + R_{t-1}^x \frac{X_{t-1}^h}{P_t} + \tau_t$$

where τ_t represents a series of payments –not internalized by the household– that firms and the fiscal authority transfer to the household such that $c_t = y_t$ in every period. In addition, notice that the budget constraint is in real terms because everything is divided over P_t. You can notice that because

$$\begin{aligned}
\int_0^1 \frac{P_{i,t}}{P_t} c_{i,t} di &= \int_0^1 p_{i,t} c_{i,t} di \\
&= \int_0^1 p_{i,t} \left(\frac{p_{i,t}}{\tilde{p}_t}\right)^{-\eta} s_{i,t-1}^{\theta(1-\eta)} q_t di \\
&= \tilde{p}_t^{\eta} q_t \int_0^1 p_{i,t}^{1-\eta} s_{i,t-1}^{\theta(1-\eta)} di \\
&= \tilde{p}_t^{\eta} q_t \tilde{p}_t^{1-\eta} \\
&= \tilde{p}_t q_t
\end{aligned}$$

Moreover, it can be also proved that

$$\tilde{p}_t q_t = c_t = y_t$$

The first equality holds because –invoking symmetry– we have that $\tilde{p}_t = s^{\theta}_{t-1}$ and $s^{\theta}_{t-1} q_t = c_t$. The second equality holds because it is assumed that the firm is committing to produce $y_{i,t} = c_{i,t}$ regardless of $a_{i,t}$.

Set up the Lagrangian,

$$L = \mathbb{E}_t \sum_{s=0}^{\infty} \beta^s \Bigg\{ \frac{q_{t+s}^{1-\gamma_q}}{1-\gamma_q} + \chi_n \log(1 - n_{t+s}) + \chi_x \log\left(\frac{X^h_{t+s-1}}{P_{t+s}}\right)$$
$$+ \lambda_{t+s}\left[w_{t+s} n_{t+s} + R_{t+s-1}\frac{B_{t+s-1}}{P_{t+s}} + R^x_{t+s-1}\frac{X^h_{t+s-1}}{P_{t+s}} + \tau_{t+s} - \tilde{p}_{t+s} q_{t+s} - \frac{B_{t+s}}{P_{t+s}} - \frac{X^h_{t+s}}{P_{t+s}}\right]\Bigg\}$$

FOC for q_t is,

$$q_t^{-\gamma_q} - \lambda_t \tilde{p}_t = 0 \qquad \Rightarrow \qquad \lambda_t = \frac{q_t^{-\gamma_q}}{\tilde{p}_t}.$$

FOC for n_t is,

$$-\frac{\chi_n}{1-n_t} + \lambda_t w_t = 0 \qquad \Rightarrow \qquad \frac{w_t}{\tilde{p}_t} = q_t^{\gamma_q}\frac{\chi_n}{1-n_t}.$$

FOC for B_t is,

$$-\lambda_t \frac{1}{P_t} + \beta\,\mathbb{E}_t\left[\lambda_{t+1}\frac{R_t}{P_{t+1}}\right] = 0 \quad \Rightarrow \quad 1 = \mathbb{E}_t\left[m_{t+1}\frac{R_t}{\pi_{t+1}}\right]$$

where $\pi_{t+1} = P_{t+1}/P_t$ and $m_{t+1} = \beta\, \tilde{p}_t/\tilde{p}_{t+1}\, (q_{t+1}/q_t)^{-\gamma_q}$.

FOC for X^h_t is,

$$\beta\frac{\chi_x}{X^h_t} - \lambda_t\frac{1}{P_t} + \beta\,\mathbb{E}_t\left[\lambda_{t+1}\frac{1}{P_{t+1}}R^x_t\right] = 0 \quad \Rightarrow \quad 1 = \beta\chi_x\frac{\tilde{p}_t q_t^{\gamma_q}}{x^h_t} + \frac{R^x_t}{R_t}.$$

where $x_t^h = \frac{X_t^h}{P_t}$ and $R_t = \pi_{t+1}/m_{t+1}$. This yields the following demand for real liquid assets:

$$x_t^h = \beta \chi_x \frac{R_t}{R_t - R_t^x} \lambda_t^{-1}.$$

A.7.3 Firm profit maximization problem

Set up the Lagrangian

$$\begin{aligned}
L = \mathbb{E}_0 \sum_{t=0}^{\infty} m_t \Bigg\{ & d_{i,t} + \kappa_{i,t} \left[\left(\frac{A_t}{a_{i,t}} n_{i,t} \right)^{\alpha} - \phi - c_{i,t} \right] \\
& + \xi_{i,t} \Bigg[p_{i,t} c_{i,t} - w_t n_{i,t} - \frac{\gamma_p}{2} \left(\pi_t \frac{p_{i,t}}{p_{i,t-1}} - \pi_{ss} \right)^2 c_t + R_{t-1}^x \frac{X_{i,t-1}^f}{P_t} + g\left(\frac{X_{i,t-1}^f}{P_t} \right) \\
& - \frac{X_{i,t}^f}{P_t} - d_{i,t} + \varphi_t \min\{0, d_{i,t}\} \Bigg] \\
& + \nu_{i,t} \left[\left(\frac{p_{i,t}}{\tilde{p}_t} \right)^{-\eta} s_{i,t-1}^{\theta(1-\eta)} q_t - c_{i,t} \right] + \lambda_{i,t} \left[\rho s_{i,t-1} + (1-\rho) c_{i,t} - s_{i,t} \right] \Bigg\}
\end{aligned}$$

FOC for $d_{i,t}$:

$$\xi_{i,t} = \begin{cases} 1 \;\text{ if }\; d_{i,t} \geq 0 \\[2ex] 1/(1-\varphi_t) \;\text{ if }\; d_{i,t} < 0 \end{cases}$$

where, in aggregate,

$$\xi_t = \mathbb{E}_t^a[\xi_{i,t}] = \int_0^{\bar{a}_t} dF(a) + \int_{\bar{a}_t}^{\infty} \frac{1}{1-\varphi_t} dF(a) = 1 + \left[\frac{\varphi_t}{1-\varphi_t} \right] [1 - \Phi(\bar{z}_t)]$$

where $\bar{a}_t$ is the value of idiosyncratic productivity $a_{i,t}$ such that $d_{i,t} = 0$:

$$c_t - w_t n_t - \frac{\gamma_p}{2}(\pi_t - \pi_{ss})^2 c_t + R_{t-1}^x x_{t-1}^f + g(x_{t-1}^f) - x_t^f = 0,$$

from the production function,

$$n_t = \frac{a_t}{A_t}(c_t + \phi)^{\frac{1}{\alpha}}.$$

Substitute n_t into the flow-of-funds constraint with $d_t = 0$. This yields,

$$c_t - w_t \frac{\bar{a}_t}{A_t}(c_t + \phi)^{\frac{1}{\alpha}} - \frac{\gamma_p}{2}(\pi_t - \pi_{ss})^2 c_t + R^x_{t-1} x^f_{t-1} + g(x^f_{t-1}) - x^f_t = 0,$$

which is

$$\bar{a}_t = \frac{1}{(c_t + \phi)^{\frac{1}{\alpha}}} \frac{A_t}{w_t} \left\{ c_t \left[1 - \frac{\gamma_p}{2}(\pi_t - \pi_{ss}) \right] + R^x_{t-1} x^f_{t-1} + g(x^f_{t-1}) - x^f_t \right\}$$

and, finally, since $\log a_t \sim N(-0.5\sigma^2, \sigma^2)$

$$\bar{z}_t = \frac{1}{\sigma}(\log \bar{a}_t + 0.5\sigma^2).$$

FOC for $n_{i,t}$:

$$\kappa_{i,t} \alpha \left(\frac{A_t}{a_{i,t}} n_{i,t} \right)^{\alpha - 1} \frac{A_t}{a_{i,t}} - \xi_{i,t} w_t = 0$$

which is

$$\kappa_{i,t} = \xi_{i,t} a_{i,t} \left(\frac{w_t}{\alpha A_t} \right) (c_{i,t} + \phi)^{\frac{1-\alpha}{\alpha}}$$

which, in aggregate, is

$$\kappa_t = \mathbb{E}^a_t [\xi_{i,t} a_{i,t}] \left(\frac{w_t}{\alpha A_t} \right) (c_t + \phi)^{\frac{1-\alpha}{\alpha}}$$

where $E_t^a[\xi_{i,t}a_{i,t}] = 1 + \varphi_t/(1-\varphi_t)[1-\Phi(\bar{z}_t - \sigma)]$.

FOC for $c_{i,t}$:

$$-\mathbb{E}_t^a[\kappa_{i,t}] + \mathbb{E}_t^a[\xi_{i,t}]p_{i,t} - \mathbb{E}_t^a[\nu_{i,t}] + (1-\rho)\,\mathbb{E}_t^a[\lambda_{i,t}] = 0$$

which is

$$\mathbb{E}_t^a[\nu_{i,t}] = \mathbb{E}_t^a[\xi_{i,t}]p_{i,t} - \mathbb{E}_t^a[\kappa_{i,t}] + (1-\rho)\,\mathbb{E}_t^a[\lambda_{i,t}]$$

which, in aggregate, is

$$\nu_t = \xi_t - \kappa_t + (1-\rho)\lambda_t.$$

FOC for $s_{i,t}$:

$$\theta(1-\eta)\,\mathbb{E}_t^a\left[m_{t+1}\nu_{i,t+1}\left(\frac{p_{i,t+1}}{\tilde{p}_{t+1}}\right)^{-\eta} s_{i,t}^{\theta(1-\eta)-1} q_{t+1}\right] - \mathbb{E}_t^a[\lambda_{i,t}] + \rho\,\mathbb{E}_t^a[m_{t+1}\lambda_{i,t+1}] = 0$$

which is

$$\mathbb{E}_t^a[\lambda_{i,t}] = \rho\,\mathbb{E}_t^a[m_{t+1}\lambda_{i,t+1}] + \theta(1-\eta)\,\mathbb{E}_t^a\left[m_{t+1}\nu_{i,t+1}\frac{c_{i,t+1}}{s_{i,t}}\right]$$

which, in aggregate, is

$$\lambda_t = \rho\,\mathbb{E}_t[m_{t+1}\lambda_{t+1}] + \theta(1-\eta)\,\mathbb{E}_t\left[m_{t+1}\nu_{t+1}\frac{c_{t+1}}{s_t}\right].$$

FOC for $p_{i,t}$:

$$\mathbb{E}_t^a[\xi_{i,t}]\left[c_{i,t}-\gamma_p\left(\pi_t\frac{p_{i,t}}{p_{i,t-1}}-\pi_{ss}\right)\frac{\pi_t}{p_{i,t-1}}c_t\right]$$
$$-\mathbb{E}_t^a\left[m_{t+1}\xi_{i,t+1}\gamma_p\left(\pi_{t+1}\frac{p_{i,t+1}}{p_{i,t}}-\pi_{ss}\right)\pi_{t+1}\frac{p_{i,t+1}}{p_{i,t}^2}c_{t+1}\right]+\eta\,\mathbb{E}_t^a[\nu_{i,t}]\left(\frac{p_{i,t}}{\tilde{p}_t}\right)^{-\eta-1}\frac{1}{\tilde{p}_t}s_{i,t-1}^{\theta(1-\eta)}q_t=0$$

which is

$$\mathbb{E}_t^a[\xi_{i,t}]\left[c_{i,t}-\gamma_p\left(\pi_t\frac{p_{i,t}}{p_{i,t-1}}-\pi_{ss}\right)\frac{\pi_t}{p_{i,t-1}}c_t\right]$$
$$-\mathbb{E}_t^a\left[m_{t+1}\xi_{i,t+1}\gamma_p\left(\pi_{t+1}\frac{p_{i,t+1}}{p_{i,t}}-\pi_{ss}\right)\pi_{t+1}\frac{p_{i,t+1}}{p_{i,t}^2}c_{t+1}\right]+\eta\,\mathbb{E}_t^a[\nu_{i,t}]\frac{c_{i,t}}{p_{i,t}}=0$$

which, in aggregate, is

$$\xi_t\big[c_t-\gamma_p\big(\pi_t-\pi_{ss}\big)\pi_t c_t\big]-\mathbb{E}_t\left[m_{t+1}\xi_{t+1}\gamma_p\big(\pi_{t+1}-\pi_{ss}\big)\pi_{t+1}c_{t+1}\right]+\eta\nu_t c_t=0$$

which is

$$\xi_t\big[1-\gamma_p\big(\pi_t-\pi_{ss}\big)\pi_t\big]-\mathbb{E}_t\left[m_{t+1}\xi_{t+1}\gamma_p\big(\pi_{t+1}-\pi_{ss}\big)\pi_{t+1}\frac{c_{t+1}}{c_t}\right]+\eta\nu_t=0$$

which is

$$1=\gamma_p\big(\pi_t-\pi_{ss}\big)\pi_t-\mathbb{E}_t\left[m_{t+1}\frac{\xi_{t+1}}{\xi_t}\gamma_p\big(\pi_{t+1}-\pi_{ss}\big)\pi_{t+1}\frac{c_{t+1}}{c_t}\right]+\eta\frac{\nu_t}{\xi_t}=0.$$

FOC for $X^f_{i,t}$:

$$-\mathbb{E}^a_t[\xi^f_{i,t}]\frac{1}{P_t} + \mathbb{E}^a_t\left\{m_{t+1}\xi^f_{i,t+1}\left[R^x_t\frac{1}{P_{t+1}} + g'\left(\frac{X^f_{i,t}}{P_t}\right)\frac{1}{P_{t+1}}\right]\right\} = 0$$

which is

$$1 = \mathbb{E}^a_t\left\{\frac{m_{t+1}}{\pi_{t+1}}\frac{\xi_{i,t+1}}{\xi_{i,t}}\left[R^x_t + g'(x^f_{i,t})\right]\right\},$$

where $x^f_t = X^f_t/P_t$. This, in aggregate, yields

$$1 = \mathbb{E}_t\left\{\frac{\xi_{t+1}}{\xi_t}\frac{R^x_t + g'(x^f_t)}{R_t}\right\},$$

where $g(x) = \zeta_x x^{1-\iota}/(1-\iota)$ with $\iota \in (0,1)$. We can isolate the real value of liquid assets x^f_t to obtain the demand for liquid assets,

$$x^f_t = \mathbb{E}_t\left\{\zeta_x^{\frac{1}{\omega}}\left[\frac{\xi_{t+1}}{\xi_t R_t - \xi_{t+1}R^x_t}\right]^{\frac{1}{\omega}}\right\}$$

where x^f_t is increasing in ζ_x (firm has more appetite for x^f_t), $E^a_t[\xi_{t+1}]$ (firm needs more resources in future), and R^x_t (interest on liquid assets pay better); and is decreasing in ξ_t (firm needs more resources today) and R_t (the households wants more resources from the firm today since they want to save in bonds as they pay better).

A.7.4 Derivation of the Phillips curve

Given the first order condition, after aggregation, for $p_{i,t}$:

$$\gamma_p\big(\pi_t - \pi_{ss}\big)\pi_t = \mathbb{E}_t\left[m_{t+1}\frac{\xi_{t+1}}{\xi_t}\gamma_p\big(\pi_{t+1} - \pi_{ss}\big)\pi_{t+1}\frac{c_{t+1}}{c_t}\right] - \eta\frac{\nu_t}{\xi_t} = 0,$$

take the total differential:

$$\gamma_p\big[\pi_{ss}\partial\pi_t{+}(\pi_{ss}{-}\pi_{ss})\partial\pi_t\big] = \mathbb{E}_t\left[m_{ss}\frac{\xi_{ss}}{\xi_{ss}}\gamma_p\partial\pi_{t+1}\pi_{ss}\frac{c_{ss}}{c_{ss}}{+}(\pi_{ss}{-}\pi_{ss})\Theta_t\right]{+}\eta\frac{\nu_{ss}}{\xi_{ss}}\left(\frac{\partial\xi_t}{\xi_{ss}}{-}\frac{\partial\nu_t}{\nu_{ss}}\right)$$

which is,

$$\hat{\pi}_t = \beta\,\mathbb{E}_t\left[\hat{\pi}_{t+1}\right] + \tilde{\eta}(\hat{\xi}_t - \hat{\nu}_t)$$

where ∂x_t is the differential of variable x_t, $\hat{x}_t = \partial x_t/x_{ss}$, π_{ss} is equal to one, m_{ss} is equal to β, and $\tilde{\eta} = (\eta\nu_{ss})/(\gamma_p\xi_{ss}) > 0$.

Appendix B

What are the Sources of boom-Bust Cycles?

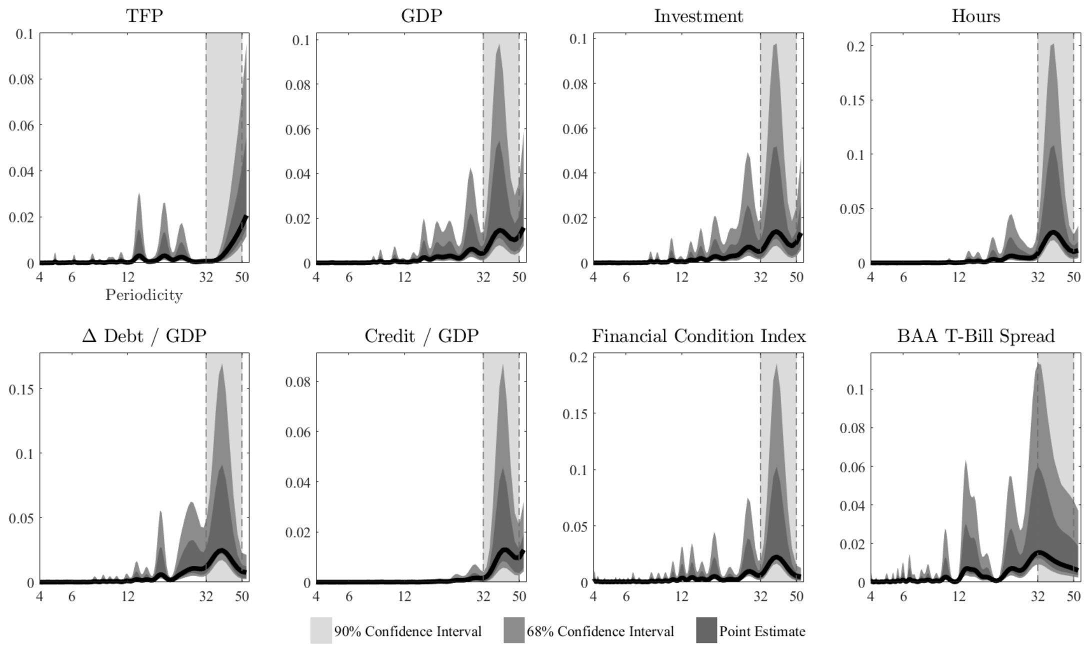


Figure B.1: Unconditional spectral density of quarterly and seasonally adjusted U.S. macroeconomic and financial variables from 1981 to 2018.

Note: All variables are stationarized using Band-Pass filter excluding periodicities above 100 quarters. Confidence intervals are computed following the procedure described in Beaudry et al. (2019).

B.1 Unconditional Spectral Density

B.2 Spectral density from model simulated data

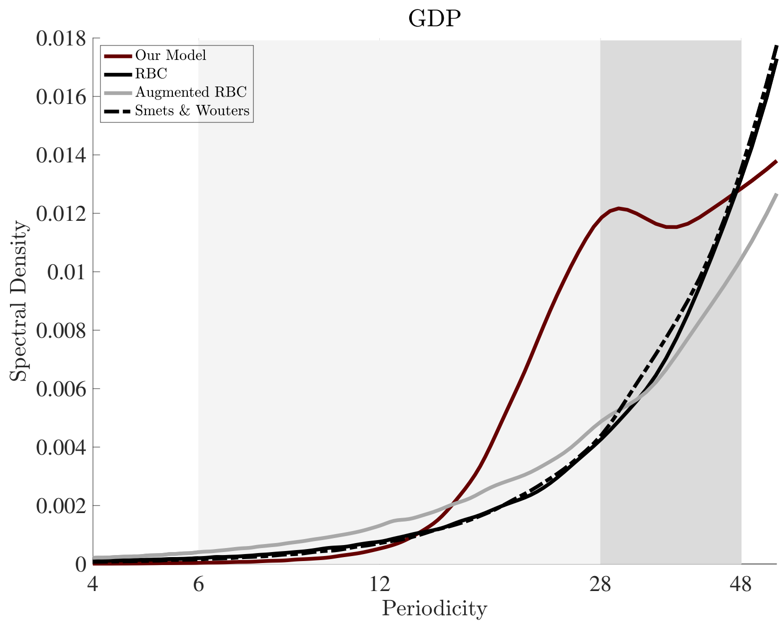


Figure B.2: Mean unconditional spectral density of GDP

Note: Monte Carlo simulation using various standard models and our model (red line). Simulated data are detrended using a band-pass filter that removes fluctuations at periodities greater than 100 quarters.

B.3 Robustness checks on technology Shocks

Figure B.5 reports impulse responses together with conditional spectral densities implied by a technology shock for the baseline specification presented in Figure 2.3 and a series of robustness checks. In particular, RC 1 and RC 2 are the first and the second robustness check where variables are linearly and quadratically detrended, respectively. RC 3 is the third robustness check where TFP is controlled using 8 lags of TFP, the first 2 principal components and news shocks. RC 4 is the last robustness check where we use different number of lags and principal component when we estimate LP impulse responses.

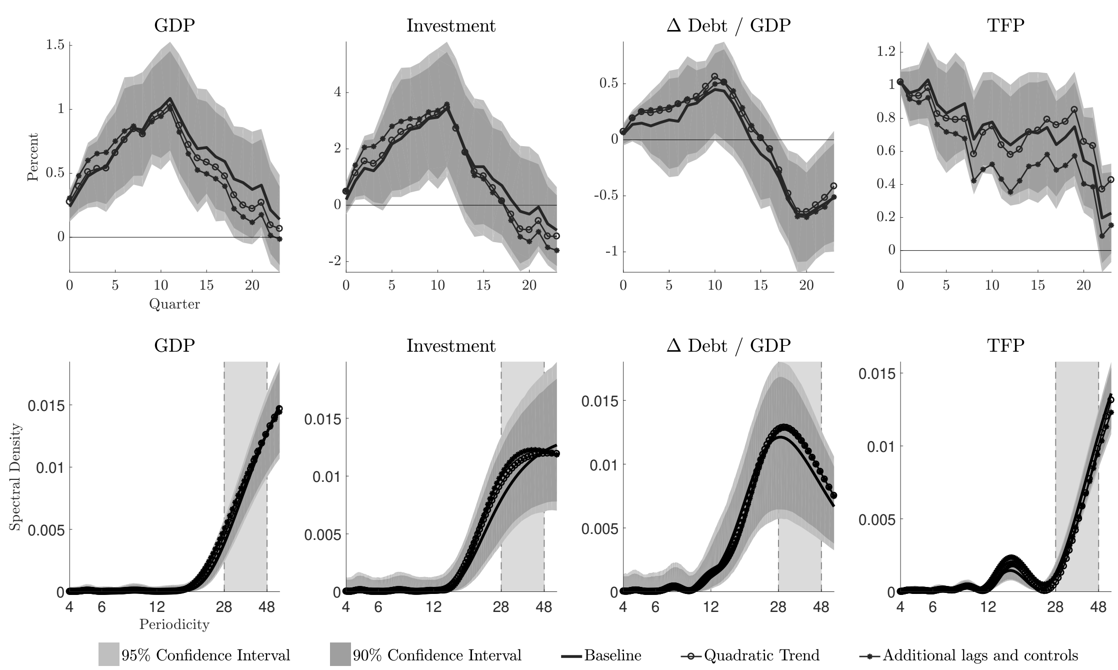


Figure B.3: Impulse responses and conditional spectral densities implied by a technology shock.

Note: Point Estimates is the baseline specification presented in Figure 2.3. RC 1 and RC 2 are the first and the second robustness check where variables are linearly and quadratically detrended, respectively. RC 3 is the third robustness check where we add more controls when we estimate a technology shock. RC 4 is the last robustness check where we use different number of lags and principal component when we estimate LP impulse responses.

B.4 Robustness checks on expectation shocks

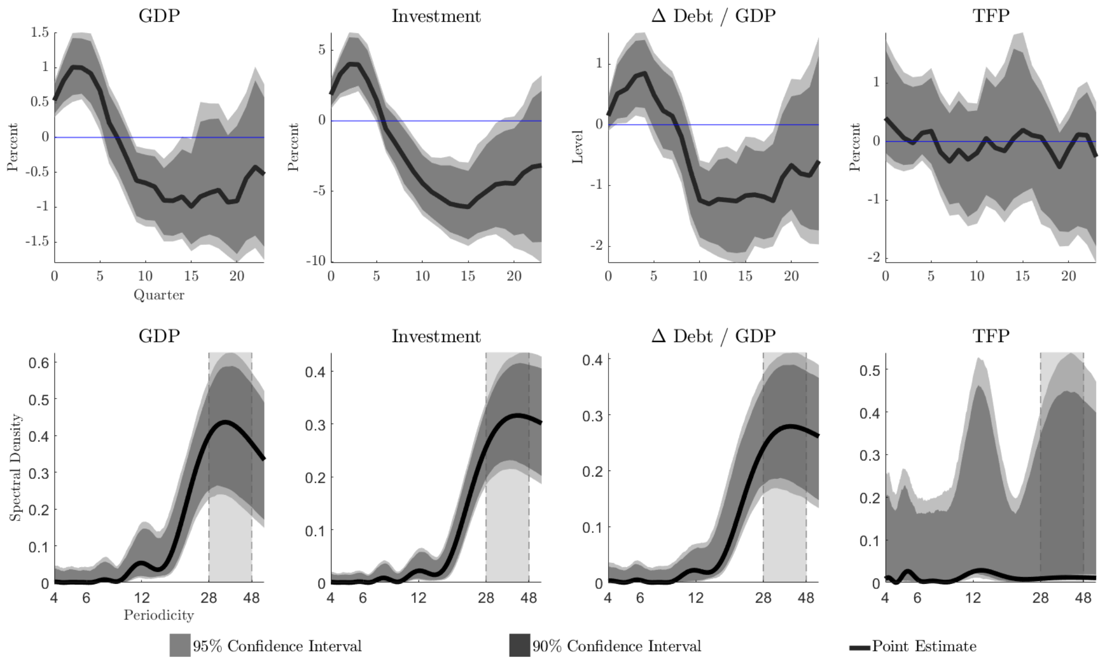


Figure B.4: Impulse responses to an expectations shock.

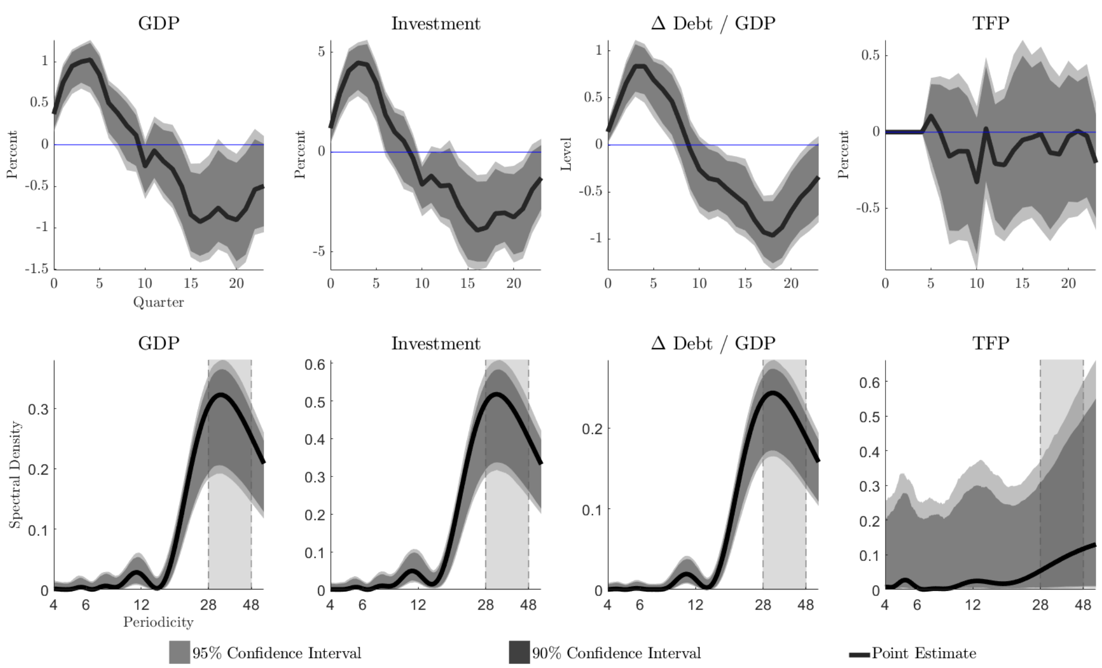


Figure B.5: Impulse responses to an expectations shock starting in 1967.

B.5 Local Projections

To estimate LP impulse responses we follow standard techniques as firstly introduced by Jordà (2005). Given the stationary series y_t and shock ε_t, impulse responses can be estimated as follows,

$$y_{t+h} = \theta_h \varepsilon_t + \sum_{j=1}^{J} \left[\delta_j \varepsilon_{t-j} + \lambda_j y_{t-j} + \gamma_j x_{t-j} \right] + \nu_{t+h} \text{ for } h = 0, 1, \ldots, H \tag{B.1}$$

where θ_h represents response of y_t to shock ε_t at horizon h and x_t are additional controls which in our estimation represent principal components from a large dataset of macroeconomic variables.

B.5.1 Inference

Following Kilian and Kim (2011) we estimate confidence interval using the block bootstrap procedure. As emphasized by Kilian and Kim (2011), we opt for this approach because the error term in the local projections regressions is most likely serially correlated. The LP impulse response estimator for horizon h depends on the tuple,

$$\mathcal{T}_h = [y_{t+h} \;\; \varepsilon_t \;\; \varepsilon_{t-1} \;\; \ldots \;\; \varepsilon_{t-J} \;\; y_{t-1} \;\; \ldots \;\; y_{t-I}] \tag{B.2}$$

To preserve the correlation in the data, build the set of all $\mathcal{T}_h$ tuples for $h = 0, 1, \ldots, H$. For each tuple $\mathcal{T}_h$, employ the following procedure:

1. Define $g = T - l + 1$ overlapping blocks of $\mathcal{T}_h$ of length l.[1]

2. Draw with replacement from the blocks to form a new tuple $\mathcal{T}_h^b$ of length T.

3. Estimate θ_h^b from $\mathcal{T}_h^b$ using LP estimator.

4. Repeat 1. to 3. B (≥ 2000) times and select confidence intervals.

B.6 Variance Decomposition

Variance decomposition is estimated following Gorodnichenko and Lee (2017). In particular, we define the population share of variance explained by the future innovations in ε_t to the total variations in the unpredictable component of y_{t+h} as,

$$v_h = \frac{\sigma_\varepsilon^2 \sum_{i=0}^{h} \theta_i}{Var(f_{t+h|t-1})} \tag{B.3}$$

where $Var(\varepsilon_t) = \sigma_{\varepsilon_t}^2$ and θ_i are LP estimators. Moreover $f_{t+h|t-1}$ can be estimated from the following regression,

$$y_{t+h} = \sum_{j=1}^{J} \delta_j \varepsilon_{t-j} + \sum_{i=1}^{I} \lambda_i y_{t-i} + \sum_{q=1}^{Q} \gamma_q x_{t-q} + f_{t+h|t-1} \tag{B.4}$$

where x_{t-q} represents a vector of additional controls.

[1] Notice that $l = (T - I - J + 2)^{\frac{1}{3}}$ is defined following Berkowitz, Birgean and Kilian (1999). Results are not sensitive to alternative choices of l.

Since the estimator v_h does not guarantee estimates to be between 0 and 1, we use the following estimator,[2]

$$\tilde{v}_h = \frac{\sigma_\varepsilon^2 \sum_{i=0}^{h} \theta_i}{\sigma_\varepsilon^2 \sum_{i=0}^{h} \theta_i + Var(\nu_{t+h} - \sum_{i=0}^{h-1} \theta_i x_{t+h-i})} \tag{B.5}$$

where ν_{t+h} is coming from the LP regression,

$$y_{t+h} = \theta_h \varepsilon_t + \sum_{j=1}^{J} \delta_j \varepsilon_{t-j} + \sum_{i=1}^{I} \lambda_i y_{t-i} + \nu_{t+h}. \tag{B.6}$$

B.6.1 Inference

To estimate confidence intervals for $\tilde{v}_h$, we directly use the non-parametric confidence intervals estimated for θ_i. In particular, use simulated θ_i^b to estimate,

$$\tilde{v}_h^b = \frac{\sigma_\varepsilon^2 \sum_{i=0}^{h} \theta_i^b}{\sigma_\varepsilon^2 \sum_{i=0}^{h} \theta_i^b + Var(\nu_{t+h} - \sum_{i=0}^{h-1} \theta_i^b x_{t+h-i})} \tag{B.7}$$

and select confidence intervals.

B.7 Conditional Spectral Density and Cyclicality Test

Consider the case where stationary variable y_t is explained by two shocks: $\varepsilon_{1,t}$ and $\varepsilon_{2,t}$. In this case, y_t can be represented with the following infinite moving average,

$$y_t = \sum_{h=0}^{\infty} \theta_{1,h} \varepsilon_{1,t-h} + \sum_{h=0}^{\infty} \theta_{2,h} \varepsilon_{2,t-h} \tag{B.8}$$

[2] See Gorodnichenko and Lee (2017) for a detailed description.

Since the estimated impulse responses cannot cover an infinite number of lags consider the truncate moving average,

$$y_t \approx \sum_{h=0}^{H} \theta_{1,h}\varepsilon_{1,t-h} + \sum_{h=0}^{H} \theta_{2,h}\varepsilon_{2,t-h} \tag{B.9}$$

Since we are interested in the conditional cyclicality implied by the two shocks, we focus on the conditional moving average,

$$y_{k,t} \approx \sum_{h=0}^{H} \theta_{k,h}\varepsilon_{k,t-h} \ \text{ for } \ k = 1, 2. \tag{B.10}$$

where $y_{k,t}$ represents the realized value of y_t only conditional on shock $\varepsilon_{k,t}$ for $k = 1, 2$.

Conditional spectral densities are parametrically estimated by taking the Fourier transform of the estimated truncated moving average. Estimators are,

$$s_k(\omega) \approx \left[\sum_{h=0}^{H} \theta_{k,h} e^{ih\omega}\right] \sigma_k^2 \left[\sum_{h=0}^{H} \theta_{k,h} e^{-ih\omega}\right] \ \text{ for } \ k = 1, 2. \tag{B.11}$$

where $\omega \in (0\ \pi]$ represents frequencies, $i = \sqrt{-1}$, $\theta_{k,h}$ is the LP estimator, and σ_k^2 is a standard estimator for $Var(\varepsilon_{k,t})$.[3]

[3] Notice that for estimating $s_k(\omega)$ we need to build a grid for $\omega \in (0\ \pi]$. Although results are not sensitive to different grid size, in our main results grid is 0.001 in order to guarantee a precise estimate to ten-year frequencies.

B.7.1 Inference

Similarly to what we have done for the variance decomposition, to estimate confidence intervals for $s_k(\omega)$, we directly use the non-parametric confidence intervals estimated for θ_h. In particular, use simulated θ_h^b to estimate,

$$s_k^b(\omega) \approx \left[\sum_{h=0}^{H} \theta_{k,h}^b e^{ih\omega}\right] \sigma_k^2 \left[\sum_{h=0}^{H} \theta_{k,h}^b e^{-ih\omega}\right] \text{ for } k = 1, 2. \tag{B.12}$$

and select confidence intervals.

B.7.2 Test

1. Filter each variable you want to test using a Band-Pass filter which excludes frequencies below 2 and above 100.

2. Estimate the autoregressive parameter ρ_y implied by this stationary variable using standard regression techniques.

3. Simulate - for each variable y - B (≥ 2000) $AR(1)$ processes with persistence parameter ρ_y fed with normally distributed random disturbances.[4]

4. For each simulated series estimate its disturbances, impulse response coefficients with LP estimator θ_h and conditional spectral density via $s_k(\omega)$ where k is the estimated innovation from each simulated $AR(1)$ process.

[4] This simulated series has the same length of the data used in the empirical section. Since our sample start slightly after 1980 then we have about 150 observations.

5. Following Canova (1998) and Beaudry et al. (2019) we test if the estimated conditional spectral densities for shocks ε_t ($\hat{s}_\varepsilon(\omega)$) are indistinguishable from the ones derived from the simulated $AR(1)$ process ($\hat{s}_a(\omega)$).

   - Notice that $H_0 : \hat{D}_\varepsilon = \hat{D}_a$ and $H_1 : \hat{D}_\varepsilon > \hat{D}_a$
   - $\hat{D}_k = \hat{s}_k(\omega_1)/\hat{s}_k(\omega_2)$
   - $\omega_1 \in (\pi/40, \pi/28)$ and $\omega_1 \in (\pi/72, \pi/48)$

6. Test statistic is estimated as follows

   - Define $\hat{D}^b_k = \hat{s}^b_k(\omega_1)/\hat{s}^b_k(\omega_2)$ as the simulation of $\hat{D}_k$ from $\hat{s}^b_k$.
   - Estimate, for each b, $\hat{\zeta}^b = \hat{D}^b_\varepsilon - \hat{D}^b_a$ as the difference between the simulation for $\hat{D}^b_\varepsilon$ and $\hat{D}^b_a$.
   - P-value is the number of $\hat{\zeta}^b > 0$ over the total number of simulations B.

	GDP	Investment	ΔDebt / GDP	TFP
Expectation Shock	3.64%	4.82%	2.24%	28.4%
Technology Shock	28.52%	5.54%	0.1%	89.84%

Table B.1: P-values for the test of a local peak in the spectral density implied by expectation shocks (first row) and technology shocks (second row).

B.8 Proof of Theorem 1

Cyclical dynamics obtain if at least two roots of the loglinearized deterministic version of the model are stable, complex and conjugate. Under equilibrium determinacy the model possess only one stable root, therefore the model does not generate cyclical dyanmics. Indeterminacy of equilibria is associated with at least an additional stable root, thus allows for the existence of complex dynamics. The loglinearized deterministic version of the model can be written as

$$\begin{pmatrix} 2\kappa d & \frac{\tau\beta\omega}{1-\tau+\tau\beta} \\ 1-\beta & \beta-\omega \end{pmatrix} \begin{pmatrix} \hat{d}_{t+1} \\ \hat{y}_{t+1} \end{pmatrix} = \begin{pmatrix} \frac{2\kappa d}{1+\mu\gamma} & M \\ 0 & 1-\omega \end{pmatrix} \begin{pmatrix} \hat{d}_t \\ \hat{y}_t \end{pmatrix} \tag{B.13}$$

where

$$M \equiv \frac{\tau\beta\omega}{1-\tau+\tau\beta} - \gamma\frac{1-\mu}{1+\gamma\mu}\left(\omega - 1 + \frac{1}{(1-\theta)(1-n)}\right) \tag{B.14}$$

With no adjustment cost of dividends, that is κ equal to zero, the dynamics of dividends is irrelevant for the evolution of y_t implying that the two eigenvalues of the system cannot be conjugate.

B.9 Data

Table B.2: Details on aggregate US data

Variable	Source and Construction	Transform
TFP	Utilization-adjusted total factor productivity (dtfp_util) by San Francisco Fed	Cumulated
GDP	Real gross domestic product (GDPC1) by FRED	Logarithmic
Investment	Gross domestic investment (GDPIC1) plus consumption of durables (PCDGCC96) by FRED	Logarithmic
Δ Debt	Flow of debt securities and loans for the nonfinancial business sector (BOGZ1FA144104005Q) by FRED	Seasonally-adjusted level
Consumption	Consumption of non-durables (PCNGC96) plus consumption of services (PCESVC96) by FRED	Logarithmic
Hours	Hours of all persons for the nonfarm business sector (HOANBS) by FRED	Logarithmic
Credit	Total credit to private non-financial sector (QUSPAM770A) by FRED	Logarithmic
GZ Credit Spread	Measured of credit spread by Gilchrist and Zakrajšek (2012) available on Simon Gilchrist's website	Level
Financial Condition Index	Chicago Fed National Financial Condition Index (NFCI) by FRED	Level
BAA T-Bond Spread	Moody's seasoned Baa corporate bond yield relative to yield on 10-year treasury constant maturity (BAA10Y) by FRED	Level

Note: Seasonally-adjusted transformation is the 7-term Henderson filter.

Following We define the after-tax model-consistent labor wedge Λ as the log difference between the MRS and MPL:

$$\Lambda_t = \log(MPL_t) - \log(MRS_t)$$

where

$$MRS_t = \frac{u_3(c_t, c_{t-1}, 1-n_t)}{u_1(c_t, c_{t_1}, 1-n_t)} \frac{1+T_t^c}{1-T_t^n} = \alpha \frac{(c_t - \iota c_{t-1})^{\omega}}{(1-n_t)^{\omega_2}} \frac{1+T_t^c}{1-T_t^n}$$

and

$$MPL_t = (1-\theta)\frac{y_t}{n_t}.$$

In order to empirically construct the labor wedge we use the same data by Zhang (2018).

Appendix C

COVID-19 and Credit Constraints

C.1 Data Appendix

Table C.1: Variable definition and sources

Variable name	Definition
$\mathbb{E}_{i,t-1}$(Sales^{g}1Y)	Pre COVID-19 expected sales growth over the next 12 months (2019 MET survey). Ordinal variable taking values: Very negative (below -15%), Negative (-15%,-5%), Constant [-5%,+5%], Positive (+5%,+15%), Very positive (above 15%).
$\mathbb{E}_{i,t}$(Sales^{g}1Y)	Post COVID-19 expected sales growth over the next 12 months (COVID-19 survey). Ordinal variable taking values: Very negative (below -15%), Negative (-15%,-5%), Constant [-5%,+5%], Positive (+5%,+15%), Very positive (above 15%).
$\mathbb{E}_{i,t-1}$(P^g)	Pre COVID-19 plans on the change in domestic prices over the next 12 months (2019 MET survey). Continuous variable.
$\mathbb{E}_{i,t}$(P^g)	Post COVID-19 plans on the change in domestic prices over the next 12 months (COVID-19 survey). Continuous variable.
$\mathbb{E}_{i,t}$(Sal^{g}3M)	Post COVID-19 expected change in sales over the next 3 months (COVID-19 survey). Continuous variable.
$\mathbb{E}_{i,t}$(Sal^{g}1Y)	Post COVID-19 expected change in sales over the next 12 months (COVID-19 survey). Continuous variable.
$\mathbb{E}_{i,t}$(Ord^g)	Post COVID-19 expected change in orders over the next 12 months (COVID-19 survey). Continuous variable.
$\mathbb{E}_{i,t}$(Emp^g)	Post COVID-19 adjustment plans on employment over the next 12 months (COVID-19 survey). Continuous variable.
$\mathbb{E}_{i,t}$(Tan^g)	Post COVID-19 adjustment plans on investment in tangibles over the next 12 months (COVID-19 survey). Continuous variable.
$\mathbb{E}_{i,t}$(Int^g)	Post COVID-19 adjustment plans on investment in tangibles over the next 12 months (COVID-19 survey). Continuous variable.
Credit constrained	Pre COVID-19 binary variable taking value of one if the firm i. did not applied for a bank loan because it would have been denied, ii. applied for a loan and it was denied, or iii. applied for a loan and it was accepted with unfavorable conditions; it takes zero otherwise (2019 MET survey).
Essential	Binary variable taking value of one if the firm i. is deemed to be essential in the 6-digit sectoral classification of of the Italian government's decree for the lockdown or ii. is deemed to be non-essential and declares to have not shut down during the lockdown; it takes zero otherwise. (COVID-19 survey and Italian government's decree of March 22).
No action	Binary variable taking value of one if the firm is not taking and not planning to take any action to face the crisis; it takes zero otherwise (COVID-19 survey).
Teleworking	Binary variable taking value of one if the firm is employing or planning to employ teleworking to face the crisis; it takes zero otherwise (COVID-19 survey).
Employment reduction	Binary variable taking value of one if the firm is reducing or planning to reduce employment to face the crisis; it takes zero otherwise (COVID-19 survey).
Hours reduction	Binary variable taking value of one if the firm is reducing or planning to reduce the amount of hours worked by its employees to face the crisis; it takes zero otherwise (COVID-19 survey).
Total shutdown	Binary variable taking value of one if the firm is shutting down or planning to shut down to face the crisis; it takes zero otherwise (COVID-19 survey).
Partial shutdown	Binary variable taking value of one if the firm is (or planning to) partially shutting down some production lines to face the crisis; it takes zero otherwise (COVID-19 survey).
Wage guarantee funds	Binary variable taking value of one if the firm is applying or planning to apply to wage guarantee funds to face the crisis; it takes zero otherwise (COVID-19 survey).

Variable name	Definition
Size	Log of assets (2018 firm balance sheets, Crif-Cribis D&B).
Age	Log of (1+) age of the firm (2019 MET survey).
Cases	Number of reported cumulative COVID-19 cases at the provincial level (https://github.com/pcm-dpc/covid-19)
Deaths	Log of (1+) COVID-19 cumulative deaths at the provincial level (imputed from number of cases, https://github.com/pcm-dpc/covid-19)
Population	Log of population at a provincial level (ISTAT).
Import	Binary variable taking value of one if the firm is an importer; it takes zero otherwise (2019 MET survey).
Export	Binary variable taking value of one if the firm is an exporter; it takes zero otherwise (2019 MET survey).
Group	Binary variable taking value of one if the firm is part of a corporate group; it takes zero otherwise (2019 MET survey).
Family firm	Binary variable taking value of one if the firm is a family business; it takes zero otherwise (2019 MET survey).
% graduated employment	Percentage of graduated employment in the firm, continuous variable (2019 MET survey).
R&D	Binary variable taking value of one if the firm performs activity of Research and Development; it takes zero otherwise (2019 MET survey).
Liquidity	Liquid assets to total assets ratio (2018 firm balance sheets, Crif-Cribis D&B).
Cash flow	Cash flow to total assets ratio (2018 firm balance sheets, Crif-Cribis D&B).
Tangible assets	Tangible assets to total assets ratio (2018 firm balance sheets, Crif-Cribis D&B).
Leverage	Total debt to equity ratio (2018 firm balance sheets, Crif-Cribis D&B).
N. of Lender Banks	Number of banks the firm is borrowing from as of January 2020 (2019 MET survey).
Lending relationship (years)	Duration of the relationship with the lender bank as of January 2020 (2019 MET survey). For firms borrowing from multiple banks (roughly 30% of the sample) this measure is computed as the equally-weighted average across the outstanding relationships.
Distance lender-bank	Distance in log-Km between the firm and the headquarter of the lender bank (2019 MET survey). For firms borrowing from multiple banks (roughly 30% of the sample) this measure is computed as the equally-weighted average across the outstanding relationships.
Trade credit	Net accounts payable (accounts payable net of accounts receivable) to total assets ratio (2018 firm balance sheets, Crif-Cribis D&B).
Credit constrained (post COVID-19)	Binary variable taking value of one if the firm expects credit constraints to be a potential issue after the COVID-19 pandemic; it takes zero otherwise (COVID-19 survey).
Concentration	two-digit sectoral Herfindahl-Hirschman Index (entire population of 2018 Italian balance sheets, Crif-Cribis D&B).
Churning	Number of exiting firms plus number of entering firms over the number of existing firms in 2018 at the two-digit sectoral level (official Italian registry data, Infocamere).

Table C.2: Descriptive Statistics

		Raw Sample					Weighted Sample				
Variable	Type	Mean	Q1	Q2	Q3	Stdev	Mean	Q1	Q2	Q3	Stdev
$\mathbb{E}_{i,t}$(Sales^{g}1Y): Very Negative	Categ.	0.440	–	–	–	–	0.489	–	–	–	–
$\mathbb{E}_{i,t}$(Sales^{g}1Y): Negative	Categ.	0.323	–	–	–	–	0.309	–	–	–	–
$\mathbb{E}_{i,t}$(Sales^{g}1Y): Constant	Categ.	0.197	–	–	–	–	0.178	–	–	–	–
$\mathbb{E}_{i,t}$(Sales^{g}1Y): Positive	Categ.	0.025	–	–	–	–	0.016	–	–	–	–
$\mathbb{E}_{i,t}$(Sales^{g}1Y): Very Positive	Categ.	0.008	–	–	–	–	0.006	–	–	–	–
$\mathbb{E}_{i,t-1}$(Sales^{g}1Y): Very Negative	Categ.	0.047	–	–	–	–	0.059	–	–	–	–
$\mathbb{E}_{i,t-1}$(Sales^{g}1Y): Negative	Categ.	0.134	–	–	–	–	0.143	–	–	–	–
$\mathbb{E}_{i,t-1}$(Sales^{g}1Y): Constant	Categ.	0.581	–	–	–	–	0.625	–	–	–	–
$\mathbb{E}_{i,t-1}$(Sales^{g}1Y): Positive	Categ.	0.208	–	–	–	–	0.151	–	–	–	–
$\mathbb{E}_{i,t-1}$(Sales^{g}1Y): Very Positive	Categ.	0.031	–	–	–	–	0.021	–	–	–	–
$\mathbb{E}_{i,t}$(P^g)	Cont.	0.047	0.000	0.000	0.100	0.147	0.071	0.000	0.000	0.100	0.183
$\mathbb{E}_{i,t-1}$(P^g)	Cont.	0.015	0.000	0.000	0.030	0.068	0.011	0.000	0.000	0.010	0.061
$\mathbb{E}_{i,t}$(Sal^{g}3M)	Cont.	-0.226	-0.300	-0.150	0.000	0.265	-0.239	-0.400	-0.150	0.000	0.294
$\mathbb{E}_{i,t}$(Sal^{g}1Y)	Cont.	-0.169	-0.250	-0.100	0.000	0.208	-0.193	-0.300	-0.100	0.000	0.234
$\mathbb{E}_{i,t}$(Ord^g)	Cont.	-0.156	-0.220	-0.100	0.000	0.221	-0.174	-0.300	-0.100	0.000	0.244
$\mathbb{E}_{i,t}$(Emp^g)	Cont.	-0.069	0.000	0.000	0.000	0.191	-0.088	0.000	0.000	0.000	0.236
$\mathbb{E}_{i,t}$(Tan^g)	Cont.	-0.139	-0.100	0.000	0.000	0.307	-0.146	-0.100	0.000	0.000	0.322
$\mathbb{E}_{i,t}$(Int^g)	Cont.	-0.121	-0.060	0.000	0.000	0.293	-0.131	-0.060	0.000	0.000	0.312
Credit constrained	Categ.	0.163	–	–	–	–	0.178	–	–	–	–
Credit constrained (post)	Categ.	0.354	–	–	–	–	0.372	–	–	–	–
Deaths	Cont.	4.143	3.018	4.114	5.046	1.552	4.207	3.077	4.162	5.046	1.639
Cases	Cont.	6.687	5.793	6.729	7.488	1.291	6.732	5.823	6.738	7.525	1.361
Population	Cont.	13.39	12.79	13.35	13.92	1.190	13.62	12.94	13.69	14.63	1.232
Essential	Categ.	0.595	–	–	–	–	0.540	–	–	–	–
Size	Cont.	14.73	13.54	14.61	15.78	1.745	13.55	12.32	13.43	14.56	1.672
Age	Cont.	3.010	2.639	3.178	3.555	0.823	2.936	2.565	3.044	3.466	0.778
Export	Categ.	0.299	–	–	–	–	0.146	–	–	–	–
Import	Categ.	0.246	–	–	–	–	0.119	–	–	–	–
R&D	Categ.	0.241	–	–	–	–	0.154	–	–	–	–
Group	Categ.	0.125	–	–	–	–	0.068	–	–	–	–
% graduated empl.	Cont.	0.112	0.000	0.000	0.117	0.220	0.154	0.000	0.000	0.083	0.315
Family firm	Categ.	0.707	–	–	–	–	0.769	–	–	–	–
Leverage	Cont.	0.667	0.506	0.704	0.855	0.234	0.643	0.446	0.675	0.866	0.262
Liquidity	Cont.	0.127	0.014	0.066	0.183	0.158	0.154	0.009	0.072	0.213	0.205
Tangible ass.	Cont.	0.211	0.037	0.143	0.329	0.207	0.197	0.014	0.079	0.313	0.241
Trade credit	Cont.	-0.111	-0.222	-0.048	0.000	0.147	-0.087	-0.149	0.000	0.000	0.141
N banks	Cont.	1.008	0.693	1.098	1.386	0.468	0.833	0.693	0.693	1.098	0.355
Length bank rel.	Cont.	0.597	0.251	0.470	0.775	0.535	0.484	0.251	0.415	0.604	0.479
Distance bank	Cont.	5.424	5.024	5.669	6.236	1.218	5.248	4.787	5.606	6.276	1.456

C.2 Other Results

Table B1: Composition of the 2019-wave MET and COVID-19 surveys.

	COVID-19 survey (1)	Met-2019 (2)
Macro Industry		
Manufacturing	63.2%	66.7%
Services	36.8%	33.3%
Size Class		
1-9 Employees	51.1%	48.1%
10-49 Employees	33.0%	34.8%
50-249 Employees	12.8%	12.5%
250 and more Employees	3.20%	4.60%
Macro Region		
Nort-West	25.1%	24.8%
Nort-East	26.6%	24.8%
Center	24.1%	25.4%
South	24.2%	25.0%

Notes: Share of firms in the sample by macro-industry, size class, and macro-geographical region. Column 1 shows the composition of the COVID-19 survey while Column 2 reports the composition of the original 2019 MET survey.

Table B2: Validation for expected sales growth

Dependent Variable:	Realized sales growth (categorical)					
	Panel A: full sample 2008–2019					
	(1)	(2)	(3)	(4)	(5)	(6)
$\mathbb{E}_{i,t-1}$(Sales^{g}1Y): Very Negative		-7.102***		-6.495***		-2.678***
		[0.0877]		[0.131]		[0.0375]
$\mathbb{E}_{i,t-1}$(Sales^{g}1Y): Negative		-2.240***		-1.572***		-1.059***
		[0.0569]		[0.0820]		[0.0216]
$\mathbb{E}_{i,t-1}$(Sales^{g}1Y): Positive		2.569***		1.986***		1.344***
		[0.0436]		[0.0639]		[0.0170]
$\mathbb{E}_{i,t-1}$(Sales^{g}1Y): Very Positive		7.028***		5.537***		3.038***
		[0.110]		[0.167]		[0.0470]
Time FE	✓	✓	✓	✓	✓	✓
Province FE	✓	✓	X	X	✓	✓
Industry (2 Digit) FE	✓	✓	X	X	✓	✓
Firm FE	X	X	✓	✓	X	X
Estimator	OLS		Within		Ordered Logit	
R-squared (Pseudo R2)	0.039	0.210	0.034	0.140	(0.017)	(0.105)
N obs.	91540	91540	91540	91540	91540	91540
	Panel B: sovereign-debt crisis only (2011)					
	(1)	(2)	(3)	(4)	(5)	(6)
$\mathbb{E}_{i,t-1}$(Sales1Y): Very Negative		-10.56***		–		-4.457***
		[0.164]		–		[0.0985]
$\mathbb{E}_{i,t-1}$(Sales1Y): Negative		-2.009***		–		-1.240***
		[0.128]		–		[0.0602]
$\mathbb{E}_{i,t-1}$(Sales1Y): Positive		2.698***		–		1.735***
		[0.110]		–		[0.0542]
$\mathbb{E}_{i,t-1}$(Sales1Y): Very Positive		5.590***		–		3.331***
		[0.404]		–		[0.231]
Province FE	✓	✓	X	X	✓	✓
Industry (2 Digit) FE	✓	✓	X	X	✓	✓
Estimator	OLS		–		Ordered Logit	
R-squared (Pseudo R2)	0.012	0.345	–	–	(0.005)	(0.155)
N obs.	14760	14760	–	–	14760	14760

Notes: the dependent variable is the realized categorical growth rate of sales. The explanatory variable is the expectations of future sales growth at the one-year horizon formed the previous period ($\mathbb{E}_{i,t-1}$(Sales^{g}1Y)). Both variables are categorical and take a value from one to five if the firm reported expected or realized sales growth to be: i. very negative (less than -15%); ii. negative (between -15% and -5%); iii. stable (between -5% and +5%); iv. positive (between 5% and 15%); and v. very positive (more than 15%). The estimator varies across columns: weighted OLS in columns 1 and 2, within estimator with firm and time fixed effects in columns 3 and 4, and weighted ordered logit (estimates) in columns 5 and 6. Standard errors (in square brackets) clustered at the province level. *, **, *** indicate statistical significance at the 10%, 5%, and 1%, respectively. In panel A we report the results for the entire sample (combination of all the waves of the MET survey), while panel B presents results for the sovereign debt crisis only (expectations formed at the end of 2011 for 2012).

Table B3: Alternative measures of geographical exposure to COVID-19

Dependent variable:	$\mathbb{E}_{i,t}(\text{Sales}^g 1\text{Y})$							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ln(Covid-19 Deaths)	-0.0489***							
	[0.0162]							
$\ln\left(\frac{\text{Covid-19 Deaths}}{\text{Population}}\right)$		-0.0489***	-0.0447**					
		[0.0162]	[0.0170]					
$\frac{\text{Covid-19 Deaths}}{\text{Population}}$				-0.0222				
				[0.0248]				
ln(Excess Deaths)					0.0143			
					[0.0375]			
$\ln\left(\frac{\text{Excess Deaths}}{\text{Population}}\right)$						0.0143	-0.00533	
						[0.0375]	[0.0304]	
$\frac{\text{Excess Deaths}}{\text{Population}}$								-0.0315
								[0.0242]
ln(Population)	0.0375	-0.0114			0.0218	0.0361		
	[0.0321]	[0.0327]			[0.0348]	[0.0400]		
R-squared	0.213	0.213	0.213	0.209	0.212	0.212	0.211	0.213
N obs.	5008	5008	5008	5008	5105	5105	5105	5105
Dependent variable:	$\mathbb{E}_{i,t}(\text{P}^g)$							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ln(Covid-19 Deaths)	2.695***							
	[0.998]							
$\ln\left(\frac{\text{Covid-19 Deaths}}{\text{Population}}\right)$		2.695***	1.401*					
		[0.998]	[0.731]					
$\frac{\text{Covid-19 Deaths}}{\text{Population}}$				0.689				
				[0.463]				
ln(Excess Deaths)					0.444			
					[0.618]			
$\ln\left(\frac{\text{Excess Deaths}}{\text{Population}}\right)$						0.444	-0.154	
						[0.618]	[0.448]	
$\frac{\text{Excess Deaths}}{\text{Population}}$								-0.213
								[0.435]
ln(Population)	0.779	3.474***			0.650	1.095		
	[0.559]	[1.186]			[0.606]	[0.802]		
R-squared	0.173	0.173	0.151	0.139	0.169	0.169	0.167	0.167
N obs.	4991	4991	4991	4991	5088	5088	5088	5088

Notes: Weighted OLS estimates. Standard errors (in square brackets) clustered at the province level. All regressions include narrow controls as well as region and industry (2 Digit) fixed effects. *, **, *** indicate statistical significance at the 10%, 5%, and 1%, respectively.

Table B4: Baseline Sales: multinomial logit

$\mathbb{E}_{i,t}(\text{Sales}^g 1\text{Y})$ Category:	Very Negative (1)	Negative (2)	Constant (3)	Positive (4)	Very Positive (5)
Deaths	0.0239*	-0.00692	-0.0171	0.00146	-0.00133
	[0.0143]	[0.0153]	[0.0115]	[0.00147]	[0.00172]
Essential	-0.206***	0.0880**	0.102***	0.0219***	-0.00640
	[0.0320]	[0.0342]	[0.0279]	[0.00579]	[0.00483]
Credit constrained	0.133**	-0.0784	-0.0525	-0.00575	0.00318
	[0.0551]	[0.0521]	[0.0509]	[0.00427]	[0.00387]
Region FE			✓		
Industry (2 Digit) FE			✓		
Wide controls			✓		
Pseudo R-squared			0.136		
N obs.			5008		

Notes: Multinomial logit (marginal effects) for weighted sample. Standard errors (in square brackets) clustered at the province level. *, **, *** indicate statistical significance at the 10%, 5%, and 1%, respectively.