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News and Financial Intermediation in Aggregate Fluctuations[*]

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March 2016

Abstract

An important disconnect in the news view of fluctuations is the lack of consistent evidence suggestive of significant macroeconomic effects of news shocks. Findings from estimated DSGE models that, in theory, allow news shocks to matter quantitatively, suggest they do not. This disconnect can be resolved once we augment a DSGE model with a financial channel that provides amplification to news shocks. Our results suggest news shocks to the future growth

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prospects of the economy to be significant drivers of U.S. fluctuations, explaining as much as 50% and 37% of the variance in hours worked and output respectively, in cyclical frequencies. *JEL Classification:* E2, E3.

1 Introduction

Motivated by the U.S. investment boom–bust episode of the 1990s, news shocks about future total factor productivity (TFP) have been proposed as a potentially important source of fluctuations (Beaudry and Portier (2004), Jaimovich and Rebelo (2009))—the so-called traditional "news" view of fluctuations. Despite its intuitive appeal, this view has faced several empirical challenges (see Beaudry and Portier (2014) for a survey). Moreover, lack of evidence in structural environments question its empirical plausibility. Specifically, a broad class of models, within the estimated DSGE methodology (Fujiwara et al. (2011), Khan and Tsoukalas (2012), Schmitt-Grohe and Uribe (2012)), suggest TFP news are very minor sources of fluctuations, a source that can be largely dismissed from business cycle analysis.[1] In this paper we show that in the post–Greenspan era (1990-2011), a DSGE model with a strong link between financial markets and real activity delivers amplification of TFP news shocks and thus provides strong support for the traditional "news" view of fluctuations.

Suitable modifications of RBC (as proposed in Jaimovich and Rebelo (2009)), and New Keynesian (NK) models (see Christiano et al. (2008), Khan and Tsoukalas (2012)) can in principle generate a boom following good news about TFP. However, those models, (a) lack transmission channels that link financial markets with real activity and (b) ignore potentially useful information contained in financial market indicators that can help in the identification of TFP news shocks. A growing literature argues that corporate bond

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[1]By contrast, using vector autoregressive (VAR) methodologies, Beaudry and Portier (2006) and Beaudry and Lucke (2010) find that TFP news shocks are important drivers of business cycles.

markets provide informative signals about future fundamentals (Gilchrist et al. (2009), Gilchrist and Zakrajsek (2012), Philippon (2009)). This paper proposes a model that links (a) and (b).

We augment a two sector NK model with a financial channel featuring leverage constraints as in Gertler and Karadi (2011) and Gertler and Kiyotaki (2010) (henceforth GK).[2] The model features a final goods (consumption) and a capital goods (investment) sector with (different) sector specific technologies. Our motivation to study a two sector model is two-fold. First, the pro-cyclicality of the relative price of investment evident in Table 1, strongly suggests the presence of at least two shocks affecting this price, namely shocks to investment specific and consumption specific technologies.[3,4] Second, examining the ability of the model to deliver sectoral co-movement, a salient feature of the business cycle, serves as a stricter test for the credibility of the "news" view.[5]

We estimate the model (using Bayesian techniques) in a post–Greenspan U.S. sample (1990-2011), allowing for many sources of uncertainty considered in the literature, using real, nominal and financial data (corporate bond spreads and bank equity). Our findings suggest news about the future growth prospects of the economy can explain a large frac-

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[2]Recent evidence (see Adrian and Shin (2010), Gilchrist and Zakrajsek (2012)) highlighting the important role of intermediaries—especially in the post 1990s—in affecting the flow of credit and determination of asset prices motivates the GK framework in our analysis.

[3]Relatedly, recent work by Basu et al. (2010) measuring sector specific technical change with a growth accounting methodology and annual industry data, find significant evidence against summarizing technology with a single aggregate index, consistent with our analysis.

[4]In one sector models, the correlations above are predicted to be strongly negative since *only* investment specific technology affects the relative price of investment (see Fisher (2006) for an illustration).

[5]See Huffman and Wynne (1999) and more recently DiCecio (2009) for evidence on sectoral co-movement.

tion of U.S. business cycles. They account for approximately 37%, 31%, 50%, 30% of the variance in output, investment, hours worked and consumption respectively, in business cycle frequencies. They also account for significant shares of the variance in nominal and financial variables. The majority of the shares reported above are accounted for by a *consumption specific* TFP news shock. The model generates broad based (aggregate) and sectoral co-movement in response to the news shock, consistent with the observed typical business cycle pattern. In response to a signal about the future productivity of (consumption sector) capital, the final goods (consumption) sector demands capital goods from the investment sector, and the latter responds by hiring more hours worked to satisfy demand, bidding up the price of investment goods and the price of capital. In the model, as in the data, corporate bond spreads decline, and activity rises following this signal. Thus the transmission favored by the data is one in which investment demand drives the cycle, consistent with the traditional "news" view (Beaudry and Portier (2004)) of fluctuations.

1.1 Model mechanisms and relation to the literature

Our model incorporates three features namely, (a) two sectors, (b) nominal price and wage rigidities and (c) financial frictions, relative to a real one sector RBC model, such as the one studied by Schmitt-Grohe and Uribe (2012) (henceforth SU). Features (b) and (c) are responsible for a radically different transmission mechanism of TFP news shocks relative to such a real model. In contrast to the findings in SU who report a very minor role, this mechanism generates a large quantitative role for TFP news shocks. We examine the impact of these features on the transmission mechanism of a TFP news shock using three model versions. We begin with a core real model of the SU variety and successively add features (b) and (c). The second model thus adds nominal price and wage rigidities to the real core and the third model (baseline) adds financial frictions on top of nominal rigidities. In effect, the first two models are restricted versions of the

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baseline.[6] All three models are estimated on the same set of observables and incorporate exactly the same number of shocks.[7] To conserve space, the details of this comparison, evaluation of model fit, along with a variance decomposition is presented in section 6. We briefly highlight however, that the baseline model has superior fit compared to the other two restricted model versions.

We consider a positive TFP shock expected to affect the productivity of the consumption sector eight quarters ahead—its the dominant news shock estimated by the baseline. The shock is normalized, so that it implies exactly the same increase in TFP in the long run in all model versions. Figure 1 depicts the transmission of the news shock on six main and sectoral macro-aggregates. In the real model (black solid line), after the first few quarters where the responses of the macro aggregates are muted, consumption and investment move in opposite directions and total hours fall, suggesting a very strong wealth effect on labor supply. This type of opposite co-movement characterizes a broad class of real (one and two sector) models, studied for example by Beaudry and Portier (2004). The adjustment in sectoral hours, illustrates the reallocation of resources from the consumption to the investment sector in order to have more capital in place when the rise in TFP eventually materializes. Thus, the real model fails to generate broad based and sectoral co-movement. When nominal rigidities are added to the real model (blue dashed line) there is a qualitative change in the transmission of the shock and all the main macro and sectoral aggregates co-move. Nominal rigidities are therefore a crucial feature that changes the transmission of TFP news shocks resulting in broad-based co-

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[6]Thus, the real model we estimate is a restricted version of our baseline model after we remove nominal rigidities, financial frictions and allow perfect capital mobility between the two sectors. It incorporates all the real frictions considered by SU. These restrictions allow it to be written as a (nested) one sector model.

[7]For comparability purposes with earlier work mentioned above, specifically SU, we include a series for utilization-adjusted aggregate TFP but exclude financial information from the estimation.

movement. With household preferences of the King et al. (1988) type, there is a wealth effect on labor supply that implies a countercyclical response of hours worked—agents feel wealthier and demand more leisure. But countercyclical price and wage mark-ups—due to nominal price and wage rigidities—produce positive shifts in labor demand and labor supply, enough to offset the wealth effect on labor supply, and hours worked rise in response to the news shock.

Finally, when financial frictions are in place in the form of constrained leveraged intermediaries (line with circles), the TFP news shock is significantly amplified relative to the restricted model with nominal rigidities but no financial frictions. The presence of leveraged financial intermediaries delivers amplification of news shocks due to the feedback loop between leveraged equity and capital prices. These intermediaries hold claims to productive capital in their portfolios. When the price of capital increases, their leverage constraint eases and their balance sheet expands. This generates a further rise in the demand for capital and a further rise in the price of capital. The demand for capital is thus amplified by leverage, bidding up the capital price relative to a standard NK model without this financial mechanism. The amplification delivers a strong lending and investment phase and a strong economy wide boom. By contrast, in a standard NK model as illustrated by Figure 1, absent this link, amplification is very weak. Section 5 provides a detailed discussion of financial amplification. Its important to note that the two sector structure does not materially affect the transmission or amplification of the news shock. As we discuss in section 5 and the on-line Appendix, the dynamics induced by a TFP news shock are qualitatively and quantitatively very similar in our baseline two sector and nested one sector NK models. Importantly, the two sector NK model has a superior fit with the data compared to the nested one sector NK model.

It is important to clarify, the financial channel is not necessary for the model to generate broad based co-movement in response to news shocks. The financial channel, as illustrated by Figure 1, is crucial however for the amplification of news shocks. We quantify this amplification with a series of exercises; in particular we show that in the

absence of the financial channel, the contribution of news shocks to the variance of macro aggregates declines substantially, consistent with earlier work using standard estimated NK models mentioned above. Importantly, the empirical fit of the model improves considerably when the financial channel is operative, providing empirical support to it.

Our paper contributes to the ongoing debate on the importance of news shocks for aggregate fluctuations and highlights a new—financial—channel that can generate significant real effects of news shocks. A related financial channel is emphasized in Gunn and Johri (2013) who investigate the role of news in the efficiency and innovation of intermediation in the financial system. This type of news is shown to be able to generate the boom-bust cycle in liquidity and economic activity observed during the Great Recession. Recent work in Christiano et al. (2014), point to news shocks in the riskiness of the corporate sector that propagate and can be identified, as in our model, having distinct implications about financial prices and quantities, through the financial sector. Other recent empirical work, that supports the news view includes, among others, Alexopoulos (2011), Leduc and Sill (2013), and Zeev and Khan (2015) while different propagation channels of news shocks are explored in Karnizova (2010), Gunn and Johri (2011), Theodoridis and Zanetti (2013), and Arezki et al. (2016).

The rest of the paper is organized as follows. Section 2 describes the model economy. Section 3 describes the empirical methodology, data, and discusses results. Section 4 quantifies the importance of news shocks as driving forces of fluctuations while Section 5 discusses the propagation of TFP news shocks. Section 6 compares our results to those of SU. Section 7 concludes.

2   The Two Sector Model

The sectors in the model produce consumption and investment goods. The latter are used as capital inputs in each sectors' production process, while the former enter only into households utility functions. Capital is sector specific. The model is sufficiently

symmetric and nests a one sector NK model once we assume, (a) capital is immediately mobile across sectors, (b) the investment sector is perfectly competitive and (c) adopt an appropriate re-normalization of TFP. Households consume, save in interest bearing deposits and supply labor on a monopolistically competitive labor market. A continuum of sector specific intermediate goods firms produce distinct investment and consumption goods using labor and capital services. They are subject to sector specific Calvo contracts when setting prices. Capital producers use investment goods and existing capital to produce new capital goods. Financial intermediaries collect deposits from households and finance capital acquisitions. A monetary policy authority controls the nominal interest rate.

2.1   Intermediate and final goods production

Intermediate goods in the consumption sector are produced by a monopolist according to the production function,

$$C_t(i) = max\left\{ A_t(L_{C,t}(i))^{1-a_c}(K_{C,t}(i))^{a_c} - A_t V_t^{\frac{a_c}{1-a_i}} F_C; 0 \right\}.$$

Intermediate goods in the investment sector are produced by a monopolist according to the production function,

$$I_t(i) = max\left\{ V_t(L_{I,t}(i))^{1-a_i}(K_{I,t}(i))^{a_i} - V_t^{\frac{1}{1-a_i}} F_I; 0 \right\},$$

where $K_{x,t}(i)$ and $L_{x,t}(i)$ denote the amount of capital services and labor services rented by firm i in sector $x = C, I$ and $a_c, a_i \in (0,1)$ denote capital shares in production.[8] The variables A_t and V_t denote the (non-stationary) level of TFP in the consumption and investment sector respectively, and $z_t = ln\left(\frac{A_t}{A_{t-1}}\right)$ and $v_t = ln\left(\frac{V_t}{V_{t-1}}\right)$ denote corresponding

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[8]Fixed costs of production, $F_C, F_I > 0$, ensure that profits are zero along a non-stochastic balanced growth path and allow us to dispense with the entry and exit of intermediate good producers (Christiano et al. (2005)). The fixed costs are assumed to grow at the same rate as output in the consumption and investment sector to ensure that they do not become asymptotically negligible.

(stationary) stochastic growth rates of TFP. For ease of exposition, these latter processes, along with all other exogenous processes introduced in various parts of the model will be described in Section 2.6.

The intermediate goods producers set prices according to Calvo (1983) contracts. In each period t, a randomly selected fraction of intermediate firms, $(1 - \xi_{p,x})$, in sector $x = C, I$ reoptimize their prices. The complementary fraction, $\xi_{p,x}$, set prices according to the indexation rules, $P_{C,t}(i) = P_{C,t-1}(i)\pi_{C,t-1}^{\iota_{pC}}\pi_C^{1-\iota_{pC}}$, $P_{I,t}(i) = P_{I,t-1}(i)\pi_{I,t-1}^{\iota_{pI}}\pi_I^{1-\iota_{pI}}\left[\left(\frac{A_t}{A_{t-1}}\right)^{-1}\left(\frac{V_t}{V_{t-1}}\right)^{\frac{1-a_c}{1-a_i}}\right]^{\iota_{pI}}$

where $\pi_{C,t} \equiv \frac{P_{C,t}}{P_{C,t-1}}$ and $\pi_{I,t} \equiv \frac{P_{I,t}}{P_{I,t-1}}\left(\frac{A_t}{A_{t-1}}\right)^{-1}\left(\frac{V_t}{V_{t-1}}\right)^{\frac{1-a_c}{1-a_i}}$ is gross inflation in the two sectors, π_C, π_I denote steady state values and ι_{pC}, ι_{pI} denote indexation parameters. The factor that appears in the investment sector expression adjusts for investment specific progress.

Final goods, C_t and I_t, in the consumption and investment sector respectively, are produced by perfectly competitive firms combining a continuum—$C_t(i)$ and $I_t(i)$—of intermediate goods, according to the technology,

$$C_t = \left[\int_0^1 (C_t(i))^{\frac{1}{1+\lambda_{p,t}^C}}di\right]^{1+\lambda_{p,t}^C}, \qquad I_t = \left[\int_0^1 (I_t(i))^{\frac{1}{1+\lambda_{p,t}^I}}di\right]^{1+\lambda_{p,t}^I},$$

The elasticities $\lambda_{p,t}^C$ and $\lambda_{p,t}^I$ are the exogenous stochastic process of (sectoral) price markup over marginal cost. As is standard in NK models, prices of final goods are CES aggregates of intermediate good prices. Details about these prices are given in the on-line Appendix C.

2.2   Households

Following Gertler and Karadi (2011), households consist of two member types, workers (relative size $1 - f$) and bankers (relative size f). Workers supply (specialized) labor, indexed by j, and earn wages while bankers manage a financial intermediary. The household thus effectively owns the intermediaries managed by its bankers, however the household does not own the deposits held by the financial intermediaries. Within a household there is perfect consumption insurance. While over time the overall proportion of bankers and

workers remains constant, household members switch between the two occupations to avoid that over time bankers can fund all investments from their own capital. In particular, bankers become workers in the next period with probability $(1 - \theta_B)$ and in this case transfer their retained earnings to their household. Workers who become new bankers are provided with start up funds by the household. The household maximizes,

$$E_0 \sum_{t=0}^{\infty} \beta^t b_t \left[\ln(C_t - hC_{t-1}) - \varphi \frac{(L_{C,t}(j) + L_{I,t}(j))^{1+\nu}}{1+\nu} \right], \quad \beta \in (0,1), \quad \varphi > 0, \quad \nu > 0,$$

where E_0 is the conditional expectation operator, β is the discount factor and h is the degree of (external) habit formation. The inverse Frisch labor supply elasticity is denoted by ν, while φ is a free parameter which allows to calibrate total labor supply in the steady state.[9] The variable b_t is a intertemporal preference shock. The household's flow budget constraint (in consumption units) is,

$$C_t + \frac{B_t}{P_{C,t}} \leq \frac{W_t(j)}{P_{C,t}}(L_{C,t}(j) + L_{I,t}(j)) + R_{t-1}\frac{B_{t-1}}{P_{C,t}} - \frac{T_t}{P_{C,t}} + \frac{\Psi_t(j)}{P_{C,t}} + \frac{\Pi_t}{P_{C,t}},$$

where B_t is holdings of risk free bank deposits, Ψ_t is the net cash flow from household's portfolio of state contingent securities, T_t is lump-sum taxes, R_t the (gross) nominal interest rate paid on deposits and Π_t is the net profit accruing to households from ownership of all firms. Notice above, the wage rate, W_t, is identical across sectors due to perfect labor mobility.

2.2.1 Household's wage setting

Each household $j \in [0,1]$ supplies specialized labor, $L_t(j)$, monopolistically as in Erceg et al. (2000). A large number of competitive "employment agencies" aggregate this specialized labor into a homogenous labor input which is sold to intermediate goods producers in

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[9]Consumption is not indexed by (j) because the existence of state contingent securities ensures that in equilibrium, consumption and asset holdings are the same for all households.

the two sectors. Aggregation is given as,

$$L_t = \left[\int_0^1 L_t(j)^{\frac{1}{1+\lambda_{w,t}}} dj \right]^{1+\lambda_{w,t}}.$$

The desired markup of wages over the household's marginal rate of substitution (or wage mark-up), $\lambda_{w,t}$, follows an exogenous stochastic process.

Profit maximization by the perfectly competitive employment agencies implies the labor demand function,

$$L_t(j) = \left(\frac{W_t(j)}{W_t} \right)^{-\frac{1+\lambda_{w,t}}{\lambda_{w,t}}} L_t, \tag{1}$$

where $W_t(j)$ is the wage received from employment agencies by the supplier of labor of type j, while the wage paid by intermediate firms for the homogenous labor input is,

$$W_t = \left[\int_0^1 W_t(j)^{\frac{1}{\lambda_{w,t}}} dj \right]^{\lambda_{w,t}}.$$

Following Erceg et al. (2000), in each period, a fraction ξ_w of the households cannot freely adjust its wage but follows the indexation rule,

$$W_{t+1}(j) = W_t(j) \left(\pi_{c,t} e^{z_t + \frac{a_c}{1-a_i} v_t} \right)^{\iota_w} \left(\pi_c e^{g_a + \frac{a_c}{1-a_i} g_v} \right)^{1-\iota_w}.$$

where, g_a, g_v denote the steady state growth rates of the z_t, v_t process respectively. The remaining fraction of households, $(1 - \xi_w)$, chooses an optimal wage, $W_t(j)$.[10] Further details on household's wage setting are given in the on-line Appendix C, as they are standard in the literature.

2.3   Capital goods production

Physical capital production. Capital is sector-specific. Our assumption is motivated by evidence in Ramey and Shapiro (2001) who report significant costs of reallocating capital across sectors. Capital producers in sector $x = C, I$, use a fraction of investment goods from final goods producers and undepreciated capital from capital services producers to produce new capital goods, subject to investment adjustment costs (IAC) as proposed

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[10]All households that can reoptimize will choose the same wage.

by Christiano et al. (2005). Solving their optimization problem yields a standard capital accumulation equation,[11]

$$\bar{K}_{x,t} = (1 - \delta_x)\xi^K_{x,t}\bar{K}_{x,t-1} + \left(1 - S\left(\frac{I_{x,t}}{I_{x,t-1}}\right)\right)I_{x,t}, \qquad x = C, I, \tag{2}$$

where δ_x denotes the sectoral depreciation rate, $S\left(\frac{I_{x,t}}{I_{x,t-1}}\right)$ denotes IAC, where $S(\cdot)$ satisfies the following: $S(1) = S'(1) = 0$, $S''(1) = \kappa > 0$, and $\xi^K_{x,t}$ is explained below.

Capital services producers. These agents purchase—using funds from intermediaries—physical capital from capital producers and transform it to capital services by choosing the utilization rate. They rent capital services—in perfectly competitive markets—to intermediate goods producers earning a rental rate equal to $R^K_{x,t}/P_{C,t}$ per unit of capital. They sell the un-depreciated portion of capital at the end of period $t + 1$ at price $Q_{x,t+1}$ back to capital producers.[12] The utilization rate, $u_{x,t}$, transforms physical capital into capital services according to

$$K_{x,t} = u_{x,t}\xi^K_{x,t}\bar{K}_{x,t-1}, \qquad x = C, I,$$

and incurs a cost denoted by $a_x(u_{x,t})$ per unit of capital. This function has the properties that in the steady state $u = 1$, $a_x(1) = 0$ and $\chi_x \equiv \frac{a''_x(1)}{a'_x(1)}$, denotes the cost elasticity.

In the transformation above, we allow for a capital quality shock (as in Gertler and Karadi (2011)), $\xi^K_{x,t}$. This disturbance shifts the demand for capital and directly affects its value—equivalently the value of assets held by intermediaries since they provide finance for capital acquisitions. For this reason we interpret it as a financial shock (see for ex-

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[11]Sector specific capital implies that installed capital is immobile between sectors. Two sector models with sector specific capital include, among others, Boldrin et al. (2001), Huffman and Wynne (1999) and Papanikolaou (2011). Limited factor mobility is shown to be able to correct many counterfactual predictions of one sector models with respect to both aggregate quantities and asset returns.

[12]The price of capital, equivalent to Tobin's marginal Q, is $Q_{x,t} = \frac{\Phi_{x,t}}{\Lambda_t}$, where Λ_t, $\Phi_{x,t}$, are the lagrange multipliers on the households' budget constraint, and capital accumulation constraint respectively.

ample, Sannikov and Brunnermeier (2014), and Gertler and Kiyotaki (2010) for a similar interpretation).

These producers solve,

$$\max_{u_{x,t+1}} \left[\frac{R^K_{x,t+1}}{P_{C,t+1}} u_{x,t+1}\xi^K_{x,t+1}\bar{K}_{x,t} - a_x(u_{x,t+1})\xi^K_{x,t+1}\bar{K}_{x,t}A_{t+1}V_{t+1}^{\frac{a_c-1}{1-a_i}} \right] \quad x = C, I.$$

Total receipts of capital services producers in period $t+1$ are equal to,

$$R^B_{x,t+1}Q_{x,t}\bar{K}_{x,t},$$

with

$$R^B_{x,t+1} = \frac{\frac{R^K_{x,t+1}}{P_{x,t+1}}\xi^K_{x,t+1}u_{x,t+1} + Q_{x,t+1}\xi^K_{x,t+1}(1-\delta_x) - a_x(u_{x,t+1})\xi^K_{x,t+1}A_{t+1}V_{t+1}^{\frac{a_c-1}{1-a_i}}}{Q_{x,t}}, \quad (3)$$

where $R^B_{x,t+1}$ is the real rate of return on capital. Since these agents finance their purchase of capital at the end of each period with funds from financial intermediaries (to be described below), $R^B_{x,t+1}$ is the stochastic return earned by the latter.

2.4   Financial sector

Financial intermediaries use deposits from households and their own equity to finance the acquisitions of physical capital by capital services producers. The financial sector in the model is a special case of Gertler and Kiyotaki (2010) where banks lend in specific islands (sectors)—they cannot switch between them. Alternatively, we can interpret the financial sector as a single intermediary with two branches, each specializing in providing financing to one sector only, where the probability of lending specialization is equal across sectors and independent across time. Due to sector specific technologies, each branch earns a sector specific return and maximizes equity from financing the specific sector.[13] Since we follow closely Gertler and Karadi (2011), we only briefly describe the essential mechanics

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[13]The specific segmentation adopted can be justified for example by the fact that within an intermediary there are divisions specializing in consumer or corporate finance.

(on-line Appendix C provides all the equations). These can be described with three key equations. The balance sheet identity, the demand for assets that links equity with the value of assets (physical capital), and finally, the evolution of equity.

The **balance sheet** (in nominal terms) of a branch that lends in sector $x = C, I$, is,

$$Q_{x,t} P_{C,t} S_{x,t} = N_{x,t} P_{C,t} + B_{x,t},$$

where $S_{x,t}$ denotes the quantity of financial claims on capital services producers held by the intermediary and $Q_{x,t}$ denotes the price per unit of claim. The variable $N_{x,t}$ denotes equity at the end of period t, $B_{x,t}$ are household deposits and $P_{C,t}$ is the consumption sector price level.

Financial intermediaries are limited from infinitely borrowing household funds by a moral hazard/costly enforcement problem, where bankers can steal funds and transfer them to households. Intermediaries maximize expected terminal wealth, i.e. the discounted sum of future equity. The moral hazard problem introduces an endogenous **leverage constraint**, limiting the bank's ability to acquire assets. This is formalized in the equation that determines the demand for assets,

$$Q_{x,t} S_{x,t} = \varrho_{x,t} N_{x,t}. \tag{4}$$

In the equation above, the value of assets which the intermediary can acquire depends on equity, $N_{x,t}$, scaled by the leverage ratio, $\varrho_{x,t}$.[14] With $\varrho_{x,t} > 1$, the leverage constraint magnifies changes in equity on the demand for assets. Higher demand for capital goods for example, which raises the price of capital, increases equity (through the balance sheet identity) which in turn brings about further changes in the demand for assets by intermediaries pushing the price of capital further. This amplification turns out to be the key reason for the important role of news shocks we recover from the estimated model.

Finally, the evolution of equity is described by the following **law of motion for**

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[14]The leverage ratio (bank's intermediated assets to equity) is a function of the marginal gains of expanding assets (holding equity constant), expanding equity (holding assets constant), and the gain from diverting assets.

equity,

$$N_{x,t+1} = \left(\theta_B[(R^B_{x,t+1}\pi_{C,t} - R_t)\varrho_{x,t} + R_t]\frac{N_{x,t}}{\pi_{C,t+1}} + \varpi Q_{x,t+1}S_{x,t+1} \right).$$

where, θ_B is the survival rate of bankers, ϖ denotes the fraction of assets given to new bankers. It is useful to define the expected (nominal) excess return (or risk premium) on assets earned by banks as

$$R^S_{x,t} = R^B_{x,t+1}\pi_{C,t+1} - R_t, \qquad x = C, I. \tag{5}$$

The presence of the financial intermediation constraint in equation (4), implies a non-negative excess return (equivalently wedge between the expected return on capital and the risk free interest rate), which varies over time with intermediaries equity.

Financing capital acquisitions by capital services producers. Capital services producers issue $S_{x,t}$ claims equal to units of physical capital acquired, $\bar{K}_{x,t}$, priced at $Q_{x,t}$. Then, by arbitrage the following constraint holds,

$$Q_{x,t}\bar{K}_{x,t} = Q_{x,t}S_{x,t},$$

where the left-hand side stands for the value of physical capital acquired and the right-hand side denotes the value of claims against this capital.[15] Using the assumptions in Gertler and Karadi (2011) we can interpret these claims as one period state-contingent bonds which allows interpreting the excess return defined in equation (5) as a corporate bond spread.

2.5 Monetary policy and market clearing

The nominal interest rate R_t, set by the monetary authority follows a feedback rule,

$$\frac{R_t}{R} = \left(\frac{R_{t-1}}{R}\right)^{\rho_R}\left[\left(\frac{\pi_{c,t}}{\pi_c}\right)^{\phi_\pi}\left(\frac{Y_t}{Y_{t-1}}\right)^{\phi_{\Delta Y}}\right]^{1-\rho_R}\eta_{mp,t}, \quad \rho_R \in (0,1), \phi_\pi > 0, \phi_{\Delta Y} > 0,$$

where R is the steady state (gross) nominal interest rate and (Y_t/Y_{t-1}) is the gross growth rate in real GDP. The interest rate responds to deviations of consumption goods

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[15]We assume—in line with Gertler and Karadi (2011)—there are no frictions in the process of intermediation between non-financial firms and banks.

(gross) inflation from its target level, and real GDP growth and is subject to a monetary policy shock $\eta_{mp,t}$. GDP (in consumption units) is defined as,

$$Y_t = C_t + \frac{P_{I,t}}{P_{C,t}} I_t + G_t,$$

where G_t denotes government spending (in consumption units) assumed to evolve exogenously according to $G_t = \left(1 - \frac{1}{g_t}\right) Y_t$, and g_t is a government spending shock. The sectoral resource constraints are as follows.

The resource constraint in the consumption sector is,

$$C_t + (a(u_{C,t})\xi_{C,t}^K \bar{K}_{C,t-1} + a(u_{I,t})\xi_{I,t}^K \bar{K}_{I,t-1})\frac{A_t V_t^{\frac{a_c}{1-a_i}}}{V_t^{\frac{1}{1-a_i}}} = A_t L_{c,t}^{1-a_c} K_{c,t}^{a_c} - A_t V_t^{\frac{a_c}{1-a_i}} F_C.$$

The resource constraint in the investment sector is,

$$I_{I,t} + I_{C,t} = V_t L_{I,t}^{1-a_i} K_{I,t}^{a_i} - V_t^{\frac{1}{1-a_i}} F_I.$$

Hours worked are aggregated as,

$$L_t = L_{I,t} + L_{C,t}.$$

Bank equity is aggregated as,

$$N_t = N_{I,t} + N_{C,t}.$$

2.6   Shocks and Information

We describe the shocks in the model and the timing assumptions that govern when agents learn about shocks. The baseline model includes the following shocks: $z_t, v_t, \lambda_{p,t}^I, \lambda_{p,t}^C, b_t, \lambda_{w,t}, \xi_{I,t}^K, \xi_{C,t}^K, \eta_{mp,t}, g_t$. They are, growth rate of TFP in the C-sector, growth rate of TFP in the I-sector, price mark-up in the I-sector, price mark-up in the C-sector, preference, wage mark-up, capital quality in the I-sector, capital quality in the C-sector, monetary policy, and government spending shock, respectively. We model the log deviations of each shock from its steady state as a first order autoregressive (AR(1)) process. The only exception is the monetary policy shock, $\eta_{mp,t}$, where we set the first order autoregressive parameter

to zero (details are provided in on-line Appendix C).

TFP news shocks. The sectoral productivity growth processes follow,

$$z_t = (1 - \rho_z)g_a + \rho_z z_{t-1} + \varepsilon_t^z, \tag{6}$$

and

$$v_t = (1 - \rho_v)g_v + \rho_v v_{t-1} + \varepsilon_t^v, \tag{7}$$

The parameters g_a and g_v are the steady state growth rates of the two TFP processes above and $\rho_z, \rho_v \in (0, 1)$ determine their persistence. We introduce a richer information structure with respect to the sectoral TFP processes. Specifically, we assume the respective innovation in the processes, (6) and (7), above consist of two components,

$$\varepsilon_t^z = \varepsilon_{t,0}^z + \varepsilon_{t,news}^z, \quad \text{and} \quad \varepsilon_t^v = \varepsilon_{t,0}^v + \varepsilon_{t,news}^v,$$

where the first component, $\varepsilon_{t,0}^x$, is unanticipated and the second component, $\varepsilon_{t,news}^x$, $x = z, v$ is anticipated or news. For example, Alexopoulos (2011) documents, people receive information (or news) in advance of the actual realization of technology innovations.[16] News can be anticipated several quarters ahead so that,

$$\varepsilon_{t,news}^x \equiv \sum_{h=1}^{H} \varepsilon_{t-h,h}^x, \quad x = z, v$$

where $\varepsilon_{t-h,h}^x$, $x = z, v$ is advanced information (or news) received by agents in period $t - h$ (equivalently h periods ahead) about the innovation that affects sectoral TFP in period t. H is the maximum horizon over which agents can receive advance information (anticipation horizon). It is assumed that the anticipated and unanticipated components for sector $x = C, I$ and horizon $h = 0, 1, \ldots, H$ are *i.i.d.* with $N(0, \sigma_{z,t-h}^2)$, $N(0, \sigma_{v,t-h}^2)$ and uncorrelated across sector, horizon and time. Note, the process above also allows for revisions in expectations. In other words, information received $t-h$ periods in advance can later be revised by updated information received at $t-h+1, \ldots t-1$, or by the unanticipated

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[16]News shocks are introduced in a similar way as for example in Schmitt-Grohe and Uribe (2012), Khan and Tsoukalas (2012) and Fujiwara et al. (2011).

component, $\varepsilon_{t,0}^v, \varepsilon_{t,0}^z$ at time t. This implies news received at any anticipation horizon may only be partially (or fail to) materialize.

3 Data and Methodology

We estimate the (log-linearized) model using quarterly U.S. data (1990 Q2 - 2011 Q1) on eleven real, nominal and financial market variables. The availability of financial information dictates the beginning of the sample. The vector of observables we use in the estimation is given as,

$$\mathbf{Y}_t = \left[\Delta \log Y_t, \Delta \log C_t, \Delta \log I_t, \Delta \log W_t, \pi_{C,t}, \pi_{I,t}, \log L_t, R_t, R_{C,t}^S, R_{I,t}^S, \Delta \log N_t\right],$$

where $Y_t, C_t, I_t, W_t, \pi_{C,t}, \pi_{I,t}, L_t, R_t, R_{C,t}^S, R_{I,t}^S, N_t$, denote, output (GDP), consumption, investment, real wage, consumption sector inflation, investment sector inflation, hours worked, nominal interest rate, consumption sector bond spread, investment sector bond spread and bank equity respectively, and Δ denotes the first-difference operator. The on-line Appendix C describes in detail the log-linearized model, steady state and measurement equations linking data and model variables.

The real and nominal variables are standard in business cycle analysis using the estimated DSGE methodology. The aggregate quantity variables are expressed in real, per capita terms using non-institutional population, ages 16 and over.[17] Our financial observables consist of sectoral (non-financial) corporate bond spreads and a publicly available measure of intermediaries' equity capital reported by the Federal Financial Institutions Examination Council. The latter refers to total equity of all insured US commercial banks—it is also expressed in real per capita terms. To arrive at the sectoral bond spread information we allocate 2-digit industries from the North American Industry Classification System (NAICS) into sectors using the year 2005 Input-Output tables. The Input-Output tables track the flows of goods and services across industries and record the final use of each industry's output into three broad categories: consumption,

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[17]For a full description of the data see the on-line data Appendix B.

investment and intermediate uses (as well as net exports and government). First, we determine how much of a 2-digit industry's final output goes to consumption as opposed to investment or intermediate uses. Then we adopt the following criterion: if the majority of an industry's final output is allocated to final consumption demand it is classified as a consumption sector; otherwise, if the majority of an industry's output is allocated to investment or intermediate demand, it is classified as an investment sector. Using this criterion, mining, utilities, transportation and warehousing, information, manufacturing, construction and wholesale trade industries (NAICS codes 21 22 23 31 32 33 42 48 49 51, except 491) are classified as the investment sector and retail trade, real estate, rental and leasing, professional and business services, educational services, health care and social assistance, arts, entertainment, recreation, accommodation and food services and other services except government are classified as the consumption sector (NAICS codes 6 7 11 44 45 53 54 55 56 81).[18]

We inform the estimation with corporate bond spreads that in principle can help to identify *news* shocks as they are likely to contain advance information over and above what can be extracted from real macroeconomic aggregates. Philippon (2009) argues that corporate bond spreads may contain news about future corporate fundamentals and provides evidence that information extracted from corporate bond markets, in contrast to the stock market, is very informative for U.S. business fixed investment. Gilchrist and Zakrajsek (2012) find that corporate bond spreads have predictive power for future GDP.

Information from corporate bond spreads. A corporate bond spread is defined as the difference between a company's corporate bond yield and the yield of a US Treasury bond with an identical maturity—information provided by Reuters' Datastream. In constructing spreads we only consider non-financial corporations and only bonds traded in the secondary market. We make the following adjustments to the spread data we con-

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[18]This information is provided by the Bureau of Economic analysis (Use Tables/Before Redefinitions/Producer Value ($http://www.bea.gov/industry/io\_annual.htm$)).

struct: using ratings from Standard & Poor's and Moody's, we exclude all bonds which are below investment grade as well as the bonds for which ratings are unavailable.[19] We further exclude all spreads with a duration below one and above 30 years and exclude all spreads below 10 and above 5000 basis points to remove the impact of outliers—consistent with the treatment in Gilchrist and Zakrajsek (2012). We assign companies into the two sectors following the procedure outlined above. The series for the sectoral spreads are constructed by taking the average over all company level spreads available in a certain quarter. The dataset contains 5381 bonds of which 1213 are classified to be issued by companies in the consumption sector and 4168 issued by companies in the investment sector. The average duration is 30 quarters (consumption sector) and 28 quarters (investment sector) with an average rating for both sectoral bond issues between BBB+ and A-.[20] It is interesting to note, our bond spread indicators appear to be quite informative, especially compared to other popular indicators—such as Baa spread, S&P 500 return—for future company fundamentals, as captured by the (I/B/E/S) long term earnings forecast.[21] Specifically, the correlation of (i) average of our two spread indicators, (ii) Baa spread, (iii) S&P 500 real return with the (I/B/E/S) earnings forecast is, -0.60^*, -0.27^*, -0.04, respectively, where $*$ indicates significance at the 5% level. These correlations suggest, our spread indicators may have the ability to strongly anticipate future changes in corporate fundamentals. A concern that may arise with our use of corporate bond spreads is that the latter may also likely reflect firm-level default risk which does not occur in equilibrium. Notice that using investment grade issuers only, likely guards

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[19]In addition to the information content of bonds spreads from high quality issuers (Gilchrist et al. (2009)), the selection of the latter, is also motivated by our modelling choice that abstracts from borrowers' balance sheet considerations in the intermediation process.

[20]The total number of firms in our sample is equal to 1696, where 516 firms belong to the consumption sector and 1180 firms belong to the investment sector.

[21]The Institutional Brokers Estimate System (I/B/E/S) long term earnings forecast aims to capture company fundamentals that are orthogonal to the current business cycle.

against this concern since holders of senior corporate debt are first in line to receive cash flows in the event of default. Nevertheless, in the robustness checks, discussed in Section 4, we introduce persistent time-varying wedges—as a proxy for factors emphasized by Gilchrist and Zakrajsek (2012)—between the observable sectoral spread series and the model implied concept and re-estimate the model.

We demean all observables prior to estimation. Removing sample means from the data guards against the possibility that counterfactual implications of the model for the low frequencies may distort inference on business cycle dynamics.[22] Del Negro et al. (2007) document this type of low frequency mis-specification in a standard estimated NK model. For example, in the sample, consumption has grown by approximately 0.32% on average per quarter, while output has grown by 0.20% on average per quarter respectively. However, the model predicts that they grow at the same rate. Thus, if we hardwire a counterfactual common trend growth rate in the two series, we may distort inference on business cycle implications that is of interest to us. We have nevertheless estimated the model without removing the means form the data. Our results are robust to this consideration (details are reported in on-line Appendix A.2). On-line Appendix B describes the data sources and methods in detail.

Prior and posterior distributions. A number of fairly standard parameters are calibrated. We set the quarterly depreciation rate to be equal across sectors, $\delta_C = \delta_I = 0.025$. From the steady state restriction $\beta = \pi_C/R$, we set $\beta = 0.9974$. The shares of capital in the production functions, a_C and a_I, are fixed at 0.3. The steady state values for the ratios of nominal investment to consumption and government spending to output are calibrated to be consistent with the average values in the data. The steady state sectoral inflation rates are set to the sample averages and the sectoral steady state mark-ups are fixed at 15%. We set the (deterministic) growth of TFPs' $g_a = 0.141\%$ and $g_v = 0.434\%$ per quarter, in line with the sample average growth rates of output in the consumption and investment sector respectively. There are three parameters specific to

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[22]A similar treatment appears, for example, in Christiano et al. (2014), Ireland (2004).

financial intermediation. The parameter θ_B, which determines the banker's average life span does not have a direct empirical counterpart and is fixed at 0.96, very similar to the value used by Gertler and Kiyotaki (2010) and Gertler and Karadi (2011). This value implies an average survival time of bankers of slightly over six years. The parameters ϖ and λ_B are fixed at values which guarantee that the steady state spread (the average of spreads across the two sectors, equal to 50 basis points) and the steady state leverage ratio matches their empirical counterparts. The steady state leverage parameter, ϱ, is fixed at 5.47. This is computed from the average ratio of assets (excluding loans to consumers, real estate and holdings of government bonds) to equity for all U.S. insured commercial banks. The on-line Appendix summarizes the calibrated parameters.

We use the Bayesian methodology to estimate parameters. Our prior distributions conform to the assumptions in Justiniano et al. (2010) and Khan and Tsoukalas (2012). We consider four and eight quarter ahead sector specific TFP news. This choice is guided by the desire to economize on the state space and consequently on parameters to be estimated while being flexible enough such that the news process is able to accommodate revisions in expectations. Similar news horizons are considered by Christiano et al. (2014), Schmitt-Grohe and Uribe (2012) and Khan and Tsoukalas (2012). The prior means assumed for the TFP news components are in line with the studies mentioned above and imply that the sum of the variance of news components is, evaluated at prior means, at most one half of the variance of the corresponding unanticipated component. We undertake robustness checks on the weight on news shocks placed by priors in section 4. Overall, the estimates are broadly consistent with earlier studies using one sector models, e.g. Smets and Wouters (2007), Khan and Tsoukalas (2012) and Justiniano et al. (2010), and we do not discuss them in detail—detailed parameter estimates are reported in the on-line Appendix, A.1.[23] One finding we draw attention to, is the degree of price

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[23]We use two tests to check for identification of the model parameters, proposed by, (i) Iskrev (2010) and (ii) Koop et al. (2013), the latter being a more powerful test in cases of weak identification. Both tests indicate that the parameters are well identified (see the

stickiness estimated for the investment sector. The Calvo probability, ξ_I, is estimated at 0.70. This implies that one of the restrictions, namely a perfectly competitive investment sector, required to write the two sector model as a particular one sector model (as in Justiniano et al. (2010), Khan and Tsoukalas (2012)) is not satisfied. The estimated volatilities for the news components imply that approximately 65% (14%) of the total variance in the innovation to the z (v) process is anticipated.

The relative fit of the baseline model. Our baseline model differs along several dimensions relative to more standard estimated NK models, e.g. Justiniano et al. (2010), found in the DSGE literature. Table 2 reports marginal likelihood statistics that speak to the relative fit and advantage of using the baseline model against plausible alternatives. The first row reports the marginal data density for the baseline model. The second row removes news shocks from the estimation. Several influential papers, including Smets and Wouters (2007), and Justiniano et al. (2010) among others, study the sources of business cycles, and consider only unanticipated shocks. The marginal likelihood statistic drops by 82 log points.[24] The third row reports the marginal likelihood statistic of a nested one sector model.[25] The reduction in the likelihood is substantial relative to the baseline, equal to 446 log points. The fourth row considers a model where news shocks are placed in the capital quality processes instead of the TFP processes. For example, GK in the context of a calibrated model consider news in capital quality, and suggest they can trigger dynamics that mimic the business cycle. The reduction in the statistic is 58 log points. Importantly, we compare the fit of the baseline model against

on-line Appendix A.3 for the details).

[24]Technically, we add an 8 quarter news (C-sector TFP) shock in the model without news components to avoid stochastic singularity caused by the number of observables > number of shocks. We have experimented with a unanticipated stationary TFP shock, introduced either in the C or I-sector instead and we obtained a roughly similar drop in the marginal likelihood metric relative to the baseline.

[25]The nested one sector model is obtained by assuming full capital mobility between the two sectors and a perfectly competitive investment sector.

a standard NK model without a financial channel. This comparison indicates that the baseline model is preferred by the data.

4   Variance Decompositions

In this section we document and discuss the relative contribution of the model's disturbances in accounting for fluctuations. Table 3 reports results from a decomposition at the frequency domain, focussing on business cycle frequencies.[26]

News shocks. TFP news shocks account for approximately 37%, 30%, 31%, 50% of the variance in output, consumption, investment and hours worked respectively, with the majority of these shares accounted for by *consumption specific* TFP news (see next section for a description of the propagation).[27]Moreover, they account for a significant fraction in the variance of both corporate bond spread series, exceeding 40%, suggesting a significant amount of variation in the latter may reflect future fundamentals. They also account for over 50% in the variance of the nominal interest rate, and between, approximately, 34% to 41% of the variance in the sectoral inflation rates. Investment specific TFP news components account for significantly smaller variance shares in all observables, namely, less than 10% (except the variance share in the real wage, approximately 17%). The finding that investment specific news shocks are of lesser quantitative importance

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[26]The decomposition is performed using the spectrum of the DSGE model and an inverse first difference filter to reconstruct the levels for output, consumption, total investment, the real wage, equity and the relative price of investment. The spectral density is computed from the state space representation of the model with 500 bins for frequencies covering the range of periodicities. For space considerations we summarize results that are of most interest to our discussion and report a detailed decomposition in on-line Appendix A.2.

[27]The on-line Appendix A.7 provides a visual inspection of the prior and posterior density functions of the share of the variance of the aggregates mentioned above accounted for by TFP news shocks.

effectively rests on the property that these shocks signal future changes in the supply not demand for capital goods. An expected improvement in the productivity of the capital goods sector, makes installed capital less valuable and generates a decline of capital prices on impact, severing the financial amplification channel which rests on procyclical capital prices. Econometrically, these shocks fail to replicate data moments, importantly, the pro-cyclicality of the relative price of investment and the counter-cyclicality of corporate bond spreads.[28]

News shocks with the financial channel turned off. The findings on the overall importance of TFP news shocks stand in contrast to earlier DSGE (Fujiwara et al. (2011), Khan and Tsoukalas (2012), Schmitt-Grohe and Uribe (2012)) work, despite many model similarities. However, the frameworks considered therein do not allow for the link between the financial sector and real activity. We now illustrate the impact of the financial channel on the empirical relevance of TFP news shocks. Table 4 reports the variance shares accounted for by TFP news shocks from two model specifications, namely, the baseline against a simple model estimated with the financial channel stripped off. This exercise helps to quantify the size of the amplification generated by the financial channel. Overall, the quantitative importance of TFP news shocks in the simpler model declines significantly. For example, the contribution of consumption specific TFP news shocks in the variance of output declines from approximately 31% in the baseline, to less than 7% in the estimated model without the financial channel, whereas the total contribution of TFP news shocks in the variance of output (hours) declines from 37% (50%) to approximately 15% (17%). In the simple model therefore, the empirical role of TFP news shocks is broadly in line (though somewhat higher) with earlier findings reported in estimated one sector NK models, such as Khan and Tsoukalas (2012), Fujiwara et al. (2011), or real frameworks such as, Schmitt-Grohe and Uribe (2012).[29] This is not surprising since our

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[28]These properties can be confirmed by examining a Figure with IRFs conditional on an investment specific news shock provided in the on-line Appendix A.4.

[29]Khan and Tsoukalas (2012) and Schmitt-Grohe and Uribe (2012) find that wage

estimated two sector model nests these simpler one sector frameworks. Section 6 provides a closer comparison of our baseline with Schmitt-Grohe and Uribe (2012), controlling for differences in observables and considering news components in all exogenous processes.

Overall, TFP (consumption and investment specific) shocks, unanticipated and news, account for the majority of the forecast error variance in the data (see the next to last column in Table 3, with the exception of C-sector inflation), thus becoming the dominant source of fluctuations. We view this finding as a success of the model since it does not have to rely excessively on non-structural disturbances to fit the data. Notably, (unanticipated) investment specific TFP shocks—in contrast to evidence from estimated one sector models (e.g. Khan and Tsoukalas (2012), Schmitt-Grohe and Uribe (2012), Christiano et al. (2014))—are sizable drivers of fluctuations, broadly consistent with earlier findings in Greenwood et al. (2000), Fisher (2006) and Justiniano et al. (2010) (see column 4 in Table 3).[30] Specifically, Justiniano et al. (2010) (henceforth JPT) conclude, in the context of a one sector estimated NK model, that shocks to the marginal efficiently of investment (MEI) are the major drivers of fluctuations. In our model, (unanticipated) investment specific TFP shocks account for 19% of output, 38% of investment and 16% of hours variance. However, when combined with investment specific news and capital quality shocks, which also affect capital accumulation similar to MEI shocks, their total contribution rises further.[31] In our model, investment specific (unanticipated and news) mark-up and preference news shocks explain a large share of the variance in the data, especially for hours worked. However, that these ad-hoc disturbances are found to explain large fractions of the variance in hours worked is not satisfactory from a structural perspective, because it likely indicates model mis-specification.

[30]The key reason, as explained in the on-line Appendix A.4, is that, in our framework, these shocks are not identified from the relative price of investment alone. This tight restriction, implicit in one sector models, is responsible for the trivial role of investment specific shocks estimated in one sector models.

[31]The contribution of capital quality shocks, which we interpret as financial shocks, is fairly limited, accounting for less than 10% in the majority of macroeconomic real and

are not estimated to be as important as estimated in JPT, primarily because they have counterfactual cyclical properties between corporate bond spreads and real variables.

Robustness. We undertake robustness to model perturbations in order to assess the sensitivity of our results regarding the empirical significance of news shocks. Briefly, we find, in line with our baseline results, TFP news shocks continue to be significant drivers of business cycles, suggesting their identification is robust across all of these model perturbations. The details and results from these robustness checks are reported in the on-line Appendix A.6.

5 Propagation and amplification of consumption specific TFP news

In this section, we discuss how the model propagates the empirically dominant consumption specific TFP news shock. Figure 2 shows impulse responses (IRFs) to a two year ahead positive, consumption specific TFP shock. The model generates both *aggregate* and *sectoral* co-movement—an important but often overlooked feature of business cycles—in response to the news shock. The broad aggregates, namely, consumption, investment, and hours worked rise along with output in anticipation of the future improvement in TFP. The sectoral hours and investment rates, also move together with aggregate activity.[32]

The two sector structure of the model propagates the shock to the investment sector.

nominal series (except consumption), but nevertheless account for shares close to 20% in two out of the three financial observables, consistent with the interpretation we adopt for these shocks. See the on-line Appendix A.8 for a detailed discussion of capital quality shocks.

[32]We have verified that sectoral investment and hours worked exhibit strong co-movement in our sample. We do not discuss this evidence in detail but we view this finding as adding credibility to the model given that we have not attempted to match data moments from sectoral hours and investment in the estimation.

The anticipation that future productivity of capital will be permanently higher in the consumption sector creates demand for capital goods produced by the investment sector. The strong demand causes the relative price of investment to rise, consistent with the procyclicality of the relative price of investment in our sample (see Table 1). Capital prices rise as well. The price of (consumption sector) capital increases in anticipation of the expected future improvement in the productivity of capital. The price of investment sector capital increases as well: more inputs, including capital specific to this sector, will be employed in order to satisfy higher demand for investment goods from the consumption sector. Thus, both hours worked and investment goods allocated to the investment sector rise. Bond spreads decline as they signal the future improvement in TFP, consistent with the time path of capital prices.[33] As we explain shortly, the strong rise in capital prices is key for the strong propagation of the news shock.

Financial amplification. Amplification of news shocks is achieved through the impact of capital prices on intermediaries equity, which in turn generates a strong investment boom. To illustrate, Figure 3 plots IRFs to the dominant news shock from the baseline model against IRFs from an estimated model without financial intermediation (shock normalized to be of equal size). The amplification is easily detected in the amplitude of the IRFs.

Higher capital prices boost bank equity. Better capitalized banks demand more capital and this process further bids up capital prices. The strong investment demand is reflected in the relative price of investment which rises more sharply in the baseline model. Figure 3 illustrates that one significant (qualitative) difference in the dynamics of the two models are in the response of capital prices and in the credit spreads. In both models,

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[33]The sectoral bond spread in the model corresponds to the expected excess return to capital (wedge between expected return to capital and risk free rate). The expected return to capital (between time $t, t+1$) declines (capital prices are expected to fall as more capital is installed) and the risk free rate rises to produce the decline in the corporate bond spreads shown in the Figure.

capital prices rise in anticipation of the future rise in productivity. In the baseline model, due to the impact of intermediaries on the demand for capital, capital prices increase very strongly; for example, the price of consumption sector capital rises on impact by approximately nine times more compared to the standard model. Thereafter, as more capital gets installed, capital prices and the return to capital are expected to decline. In the baseline model thus, other things equal, this path of capital prices creates a very strong incentive to build capital in the very short run (before the shock materializes) which (due to immobility of installed capital), can be achieved through a strong rise in hours worked. By contrast, in the standard model capital prices increase moderately on impact, and are expected to rise further in the future—this delays somewhat investment spending as the return to capital is expected to rise in the future. Another notable difference is the behavior of inflation which rises in the baseline but declines in the model without the financial channel. We discuss this difference below.

Co-movement in response to news. Beaudry and Portier (2014) illustrate the difficulties of standard models to generate co-movement in response to news shocks. Jaimovich and Rebelo (2009) propose a solution based on preferences that can produce a positive labor supply shift with a concurrent increase in consumption. Our model generates co-movement despite featuring preferences of the King et al. (1988) type which imply a wealth effect on labor supply in response to news. This success of the model relies on the presence of nominal rigidities. Nominal (price and wage) rigidities give rise to endogenous countercyclical price and wage mark ups. We can define the sectoral labor demand and labor supply curves and the three mark-ups involved from the log-linearized model as follows,

$$\hat{w}_t = \underset{(+)}{\hat{mc}_{C,t}} - \underbrace{a_c(\hat{k}_{C,t} - \hat{L}_{C,t})}_{(MPL_C)},$$

$$\hat{w}_t = \underset{(+)}{\hat{mc}_{I,t}} - \underbrace{a_i(\hat{k}_{I,t} - \hat{L}_{I,t})}_{(MPL_I)} - \hat{p}_{i,t},$$

$$\hat{w}_t = \underset{(-)}{\hat{g}_{w,t}} - (\nu\hat{L}_t + \hat{b}_t - \hat{\lambda}_t)$$

where, $\hat{mc}_{x,t}, x = C, I$, is the real marginal cost or inverse of price mark-up, $MPL_x, x = C, I$, is the marginal product of labor, $\hat{p}_{i,t}$, is the relative price of investment, $\hat{g}_{w,t}$ is the wage mark-up, and $\nu\hat{L}_t + \hat{b}_t - \hat{\lambda}_t \equiv$ marginal rate of substitution (MRS). Countercyclical price and wage mark-ups produce positive shifts to the labor demand and labor supply curves respectively. A positive, consumption specific TFP news shock is associated with a fall in both sectoral price mark ups (i.e. the wedge between the MPL and the real wage, hence the positive sign underneath $\hat{mc}_{x,t}$), shifting sectoral labor demand to the right. The same shock implies a fall in the wage mark up (i.e. the wedge between the MRS and the real wage) shifting the labor supply to the right. Both of these forces, act to counteract the negative wealth effect on labor supply and equilibrium hours rise. The role of countercyclical mark-ups is illustrated in Figure 4.[34] Without countercyclical mark-ups it is not possible to generate positive co-movement: consumption declines, caused by a decline in hours worked employed in the consumption sector. One sector NK models featuring countercyclical mark-ups can generate co-movement in response to TFP news shocks (see e.g. Christiano et al. (2008)), but in those estimated models (Khan and Tsoukalas (2012), Fujiwara et al. (2011)), TFP news shocks are found to be very minor sources of business cycles, suggesting this mechanism alone cannot provide enough amplification.[35]

The debate on the sources of business cycles. Overall, the TFP news shock has

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[34]The Figure plots a set of IRFs where both price and wage rigidities are nearly eliminated. They are generated from the baseline model where we have set the steady state mark-ups, namely, $\lambda_p = \lambda_w = 0.01$, indexation parameters, $\iota_{pC} = \iota_{pI} = \iota_w = 0.01$, and Calvo probabilities for prices and wages, $\xi_C = \xi_I = \xi_w = 0.01$ and all other parameters at the estimated values.

[35]The on-line Appendix presents a comparison between a one sector and the baseline two sector model. The main differences can be detected in the responses of the investment and hours worked due to the fact that reallocation in the two sector model can only occur through new investment spending.

dynamics that resemble a demand shock with activity and inflation moving in the same direction. Inflation in the model is determined by current and future real marginal cost via the Phillips curve. The persistent rise in the current and future real marginal cost (inverse of the price mark-ups shown) illustrated in Figure 3 provides the clue for the rise in inflation. Financial amplification plays a critical role for this rise. Note that in the model without the financial channel inflation instead falls, as future expected marginal costs decline, especially strongly in the consumption sector. In the baseline, the strong rise in the value of capital (as explained above) implies a very strong rise in the rental rate for capital which drives the marginal cost persistently higher, over and above the increase in marginal cost caused by the rise in real wage. Influential work by Galí (1999), Ramey (2005), and Basu et al. (2006), suggests that TFP shocks may not be important sources for fluctuations and argue strongly for demand shocks which arise naturally in NK environments.[36] This debate is still alive and well. Our findings suggest that TFP shocks of the anticipated type cannot be ruled out as a source of fluctuations in NK environments—its precisely those nominal frictions that allow them to emerge as sources of fluctuations. Moreover, in extensions of NK models with news shocks and financial frictions such as the one advocated in this paper, the strong demarcation, emphasized in the literature, between real disturbances such as TFP shocks and the NK view of fluctuations which favors demand shocks, becomes blurred.

6   A comparison with Schmitt-Grohe and Uribe

As discussed in section 1.1, our finding regarding the importance of TFP news shocks is at odds with those reported by SU. These authors find that TFP news shocks are very minor sources of fluctuations. This section provides a detailed comparison based on

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[36]The conclusions regarding the (un)importance of technology shocks from this early body of work has been recently challenged by the findings in Fisher (2006), Alexopoulos (2011) and Basu et al. (2010).

the variance decomposition estimated for the baseline and real core model discussed in section 1.1. For comparability, both model versions are estimated on the following set of observables with the same shocks, including sector specific TFP news shocks,

$$\mathbf{Y}_t = \left[\Delta \log Y_t, \Delta \log C_t, \Delta \log I_t, \Delta \log W_t, \pi_{C,t}, \pi_{I,t}, \log L_t, R_t, \Delta \log TFP_t\right],$$

The first eight observables are the same as those described in section 3. The set of observables includes a quarterly measure of utilization-adjusted aggregate TFP available from John Fernald at the San Francisco Fed.[37] This measure of TFP, based on the methodology of Basu et al. (2006), is an imperfectly cleansed version of the Solow residual. It corrects for variable capacity utilization but due to lack of data in the quarterly frequency, does not correct for imperfect competition, mark-up variation as well as factor re-allocation, potential sources of high frequency measurement error, arising from the aforementioned non-technology factors. Even though the majority of estimated DSGE models studying the sources of business cycle do not consider TFP among the set of observables, we nevertheless find it instructive to include it for a precise comparison of our results with those of SU, adding a caveat regarding the exogeneity of the TFP series.

Table 5 displays the variance shares accounted for by the TFP news shocks focussing on the four main aggregates and TFP. We report both the shares in the business cycle frequencies as well as the shares of the unconditional variances of the variables, for comparability with SU who also report these latter shares. In the real model, TFP news shocks account for approximately 11%, 7%, 6% of the variance in output, investment and hours respectively, and approximately 15% of the variance in consumption in business cycle frequencies. The shares reported for the unconditional variances are very similar. They are broadly similar to those reported in SU (see Table VI, page 2757), suggesting the (near) irrelevance of TFP news shocks for business cycles. In the baseline model by contrast, news shocks account for approximately 35%, 35%, 61% of the variance in

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[37]Available from $http : //www.frbsf.org/economic-research/economists/john-fernald$. The series for TFP was downloaded in July 2015.

output, investment and hours respectively, and approximately 15% of the variance in consumption in business cycle frequencies. These numbers are broadly similar to those reported in Table 5, except consumption which in this case is lower and hours which is higher. Further, TFP news shocks account for around 40% of the variance in TFP in business cycle frequencies and around 34% in low frequencies. The shares of the unconditional variances is similar, except for hours which is markedly lower. Comparing the marginal likelihood statistic reveals a significant improvement in the fit of the baseline model compared to the real model, by 195 log points. Finally, we report results of an extended baseline model, which is estimated with news components in all exogenous processes (except monetary policy), in addition to TFP. SU also incorporate news components in all exogenous processes, therefore it is important to examine the role of TFP news in this extended specification.[38] Even though many more shocks compete in the extended model, it attributes a significant role to TFP news shocks in accounting for the variances in the observables. The shares of the unconditional variances accounted for by TFP news shocks are similar to the simple model, though it estimates a smaller role of TFP news in business cycle frequencies. Nevertheless, the simple parsimonious model has a better fit compared to the extended model, speaking to its suitability.

7 Conclusions

The empirical evaluation of the news driven view of business cycles has been challenging on both modelling and econometric front (see Beaudry and Portier (2014)). DSGE models, despite incorporating model frictions that in theory allow TFP news shocks to matter, estimate them to be un-important as sources of business cycles. In this paper we propose and empirically evaluate a financial channel that links in a parsimonious way

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[38]These authors find that news in ad-hoc disturbances such as wage mark-up and preference processes account for a large share of the variance in output, consumption and hours.

leveraged lenders, capital prices and real activity in an NK DSGE model. When we discipline this channel with information from corporate bond markets, we find that TFP news shocks are important drivers of the U.S. business cycles in the post-Greenspan era.

Our model has more desirable implications not discussed in this paper and are contained in a companion paper (see Görtz and Tsoukalas (2015)). Specifically, we suggest that the financial channel, can largely resolve the existing disagreement between VAR based and DSGE based identification methodologies over the empirical relevance of the news view.

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Table 1: Correlations: Relative price of investment and economic activity

	Hours	GDP	Investment
Relative Price Investment	0.40*	0.35*	0.26*

Sample is 1990Q2 to 2011Q1. * denotes significance at the 5% level. All variables are filtered using the HP filter with a smoothing parameter of 1600. Variables are described in the on-line Appendix B.

Table 2: Log Marginal Data Densities of Different Models

Model version	Log Marginal Likelihood
Baseline: 4 and 8 quarter ahead TFP news shocks in both sectors	-825
Model without any news components	-907
(Nested) one sector model	-1271
Model with 4 and 8 quarter news capital quality shocks only (in both sectors)	-883
Baseline model	-528
Model without financial channel	-541

Notes. The marginal data density is computed using the modified harmonic mean method proposed by Geweke (1999), based on 500,000 draws for each model after discarding the first 100,000 draws. The last two model versions are estimated without financial data.)

Table 3: Variance decomposition at posterior estimates—business cycle frequencies (6-32 quarters)

| | TFP shocks: | | | | | | financial shocks: | all other shocks | all TFP shocks | all TFP news shocks |
	z	z^4	z^8	v	v^4	v^8	sum of ξ_C, ξ_I		sum of cols. 1-6	sum of cols. 2,3,5,6
Output	0.195	0.093	0.213	0.187	0.006	0.054	0.073	0.179	0.748	0.366
Consumption	0.241	0.106	0.185	0.023	0.001	0.011	0.200	0.233	0.568	0.303
Investment	0.040	0.043	0.165	0.384	0.009	0.090	0.052	0.218	0.730	0.309
Total Hours	0.063	0.091	0.341	0.163	0.006	0.057	0.051	0.229	0.720	0.494
Real Wage	0.206	0.083	0.131	0.038	0.015	0.150	0.078	0.299	0.623	0.379
Nom. Interest Rate	0.036	0.070	0.466	0.122	0.003	0.024	0.051	0.230	0.719	0.562
C-Sector Inflation	0.006	0.017	0.231	0.103	0.007	0.079	0.014	0.543	0.443	0.334
I-Sector Inflation	0.028	0.044	0.315	0.226	0.003	0.047	0.079	0.258	0.663	0.410
C-Sector Spread	0.077	0.078	0.313	0.080	0.001	0.009	0.218	0.226	0.556	0.400
I-Sector Spread	0.093	0.083	0.329	0.140	0.001	0.029	0.004	0.321	0.675	0.442
Equity	0.190	0.088	0.324	0.056	0.002	0.008	0.187	0.145	0.668	0.422
Rel. Price of Investment	0.086	0.021	0.021	0.583	0.009	0.066	0.051	0.163	0.787	0.117

z = TFP in consumption sector, z^x = x quarters ahead consumption sector TFP news shock, v = TFP in investment sector, v^x = x quarters ahead investment sector TFP news shock, ξ_C and ξ_I = capital quality shocks in the consumption and investment sector. Business cycle frequencies considered in the decomposition correspond to periodic components with cycles between 6 and 32 quarters. We report median shares.

Table 4: Variance Decompositions—TFP News shocks: Importance of financial intermediation channel

	Baseline Model			Simple Model estimated without financial intermediation		
	C-Sector TFP News	All TFP News	All TFP Shocks	C-Sector TFP News	All TFP News	All TFP Shocks
Output	0.306	0.366	0.748	0.066	0.146	0.472
Consumption	0.291	0.303	0.568	0.103	0.300	0.739
Investment	0.208	0.306	0.730	0.045	0.133	0.649
Total Hours	0.432	0.494	0.720	0.050	0.170	0.455
Real Wage	0.215	0.379	0.623	0.062	0.209	0.48
Nom. Interest Rate	0.536	0.562	0.719	0.041	0.209	0.626
C-Sector Inflation	0.249	0.334	0.443	0.072	0.197	0.633
I-Sector Inflation	0.359	0.410	0.663	0.014	0.023	0.395
C-Sector Spread	0.390	0.400	0.556	n.a.	n.a.	n.a.
I-Sector Spread	0.412	0.442	0.675	n.a.	n.a.	n.a.
Equity	0.412	0.422	0.668	n.a.	n.a.	n.a.
Rel. Price of Investment	0.042	0.117	0.787	0.028	0.112	0.926

Notes. The simple model strips off the financial channel but is otherwise identical to the baseline. The Table reports only the variance shares accounted for by all TFP shocks, unanticipated and news, thus they sum to less than 1. Business cycle frequencies considered are computed as in Table 3. We report median shares.

Table 5: Share of variance explained by TFP news shocks

| | Real model | | Baseline model | | Extended baseline | |
	business cycle freq.	unconditional decomposition	business cycle freq.	unconditional decomposition	business cycle freq.	unconditional decomposition
Output	0.107	0.075	0.354	0.393	0.167	0.275
Consumption	0.157	0.245	0.151	0.253	0.117	0.278
Investment	0.074	0.049	0.346	0.351	0.225	0.273
Total Hours	0.057	0.069	0.612	0.241	0.230	0.253
TFP	0.147	0.176	0.409	0.337	0.365	0.322
Log Marginal Likelihood	-898		-703		-706	

Notes. The real model is a (nearly) perfectly competitive model without financial frictions. It is a restricted estimated version of the baseline model, where the steady state mark-ups, $\lambda_p = \lambda_w = 0.01$, indexation parameters, $\iota_{pc} = \iota_{pI} = \iota_w = 0.01$, and Calvo probabilities for prices and wages, $\xi_C = \xi_I = \xi_w = 0.01$. The extended baseline model is estimated with 4 and 8 ahead news components in all exogenous processes, except monetary policy shock. Business cycle frequencies are computed as in Table 3. The numbers for the unconditional decomposition are reported for the growth rates of these variables. We report median shares.
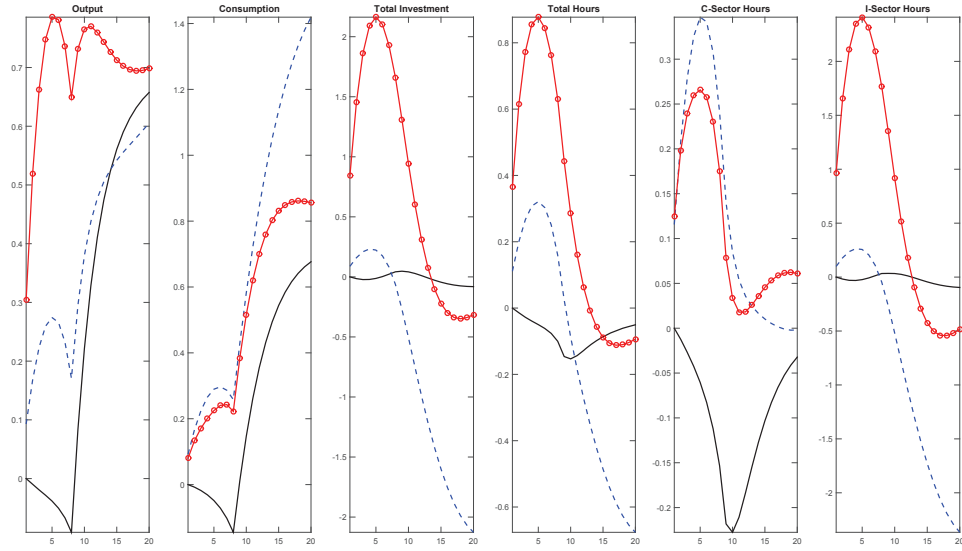
Figure 1: Responses to a consumption sector TFP news shock (anticipated 8 quarters ahead). Estimated real model (black solid line) vs. estimated real model with nominal rigidities (blue dashed line) vs. estimated baseline model (red line with circles). The horizontal axes refer to quarters and the units of the vertical axes are percentage deviations.
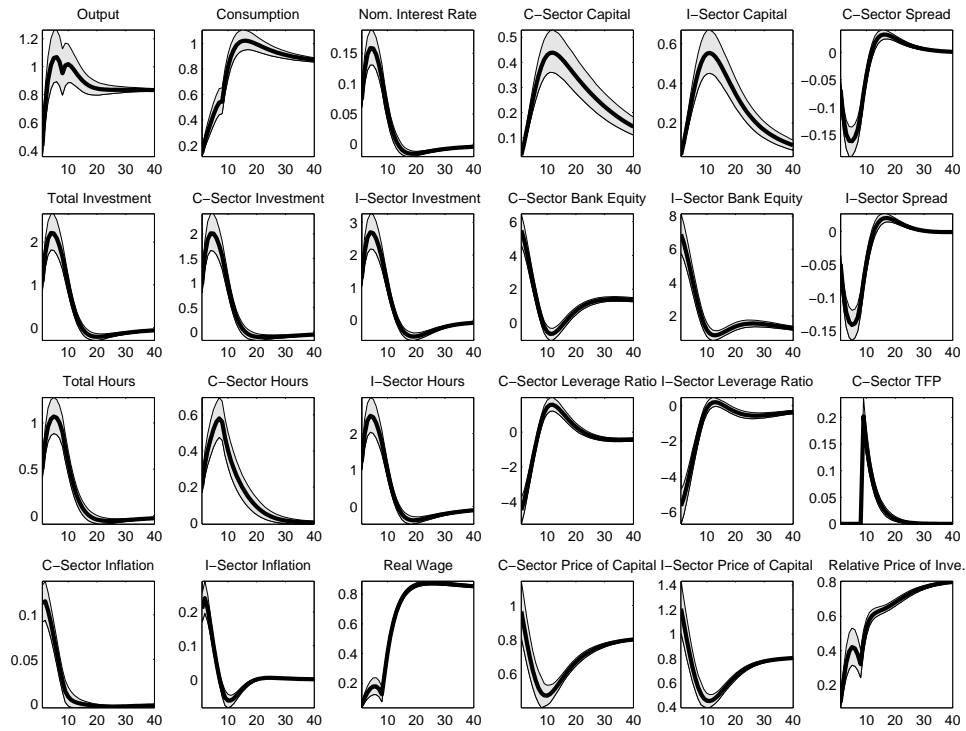
Figure 2: IRFs to a one std. deviation TFP news shock (anticipated 8 quarters ahead) in the consumption sector. Median responses with 90% confidence bands in shaded areas. The horizontal axes refer to quarters and the units of the vertical axes are percentage deviations
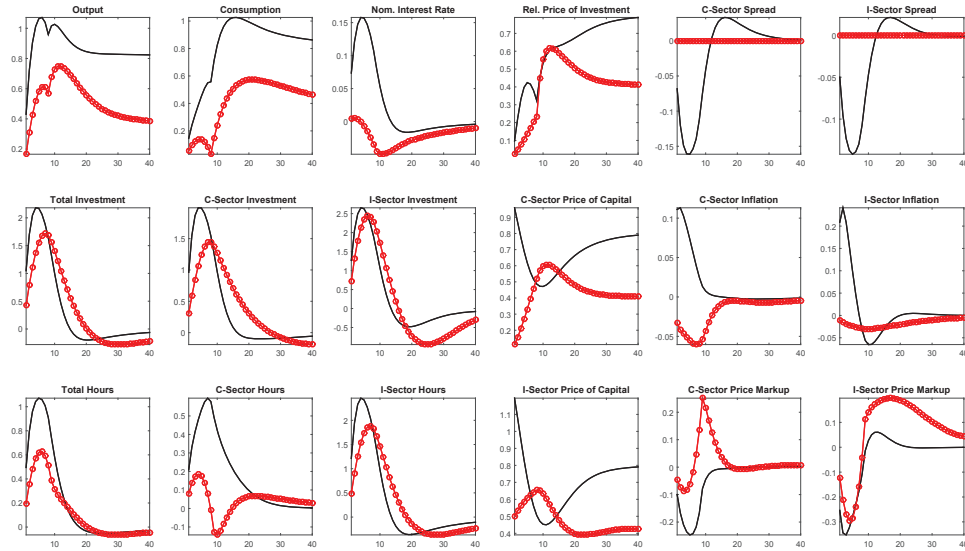
Figure 3: Responses to a one std. deviation TFP news shock (anticipated 8 quarters ahead) in the consumption sector. Baseline model with financial intermediation (black solid line), and estimated model without financial intermediation (red line with circles). The horizontal axes refer to quarters and the units of the vertical axes are percentage deviations
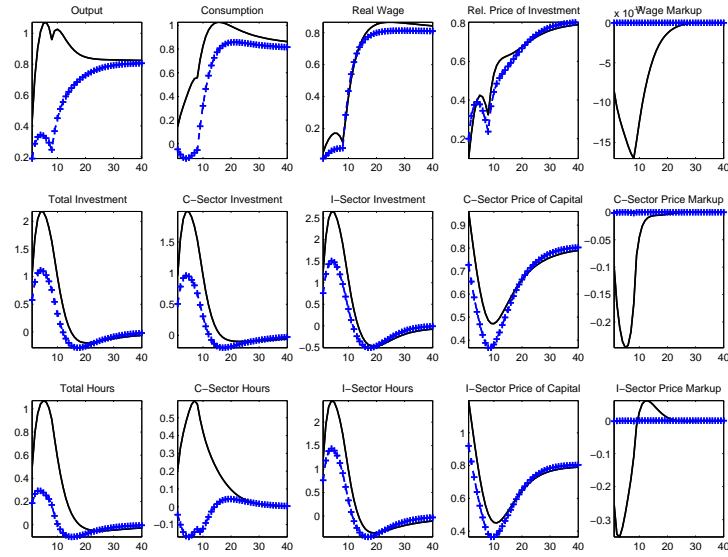
Figure 4: Responses to a one std. deviation TFP news shock (anticipated 8 quarters ahead) in the consumption sector. Baseline model (black solid line) vs. model without wage and price rigidities (line with crosses). The horizontal axes refer to quarters and the units of the vertical axes are percentage deviations.