Online Appendix:
Empirical Results and Model Analysis
(Non intended for publication)

1 Empirical Analysis

1.1 VAR evidence

I examine the empirical link between financial shocks and labor productivity using a reduced form vector autoregression (VAR) model applied to U.S. data.

To proxy for a 'financial shock' in the data, I draw from Gilchrist and Zakrajšek 2012 and use their *excess bond premium* (hencerforth *ebp*), which captures the association between measured default risk and credit spreads.

The VAR includes the following endogenous variables: (1) log-difference of total labor productivity; (2) log-difference of hours worked (non-farm business sector); (3) excess bond premium (in percentage points); and (4) the effective (nominal) federal funds rate. The full sample period is 1973q1-2010q3. To examine the differential effect of financial shocks over time, I divide the data into two subsamples (pre-84 and post-84). For the post-84 subsample I use four lags. In addition, since the pre-84 subsample is shorter (starting 1973q1) I use one lag, consistent with the AIC selection criterion.

Figure 1 shows the dynamic response of labor productivity to a 1-standard deviation increase in the *ebp* in both the post-84 subsample (left panel) and the pre-84 subsample (right panel). Notably, we find that in the post-84 period labor productivity experiences a significant and persistent short-run drop (about 1-standard deviation) when the *ebp* rises. Relatedly, in the pre-84 period there is no significant effect of financial shocks. In a similar vein, figure 2 shows the response of hours worked to an *ebp* shock. The right panel indicates that the *ebp* shock has no significant impact on hours worked in the pre-84 subsample, while the left panel shows that an *ebp* shock leads to a significant and persistent decline (about 1-percentage point) in ours hours worked.

Next, we ask: what has been the relative contribution of financial shocks to labor productivity fluctuations before and after the mid-80s? Figure 3 summarizes the contribution of *ebp* shocks to the forecast error variance of productivity and hours. Notably, the upper two panels provide evidence that the *ebp* shock has been a significant determinant of the variability of labor productivity and hours worked since 1984, while this shock had no significant effect in the pre-84 subsample.

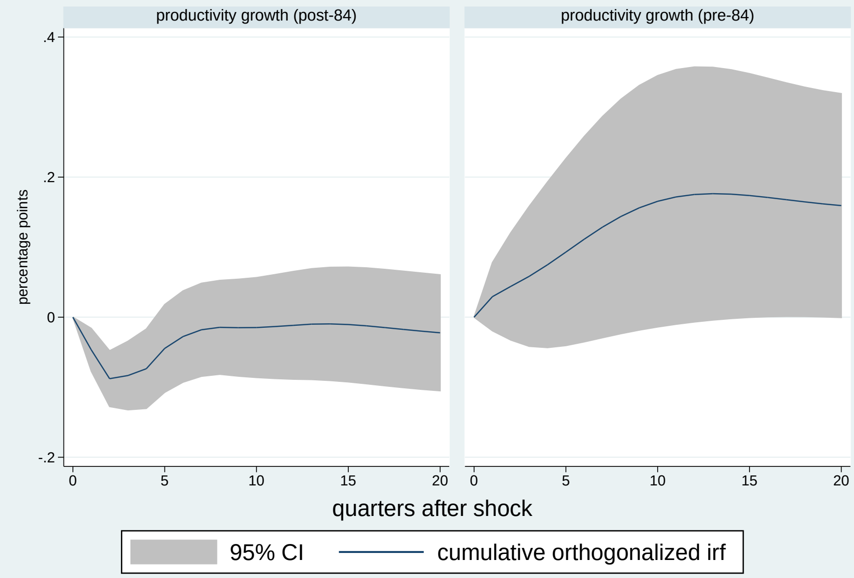

Figure 1. Dynamic response of labor productivity to financial shock (pre-84 and post-84)

Figure 2. Dynamic response of hours worked to financial shock (pre-84 and post-84)

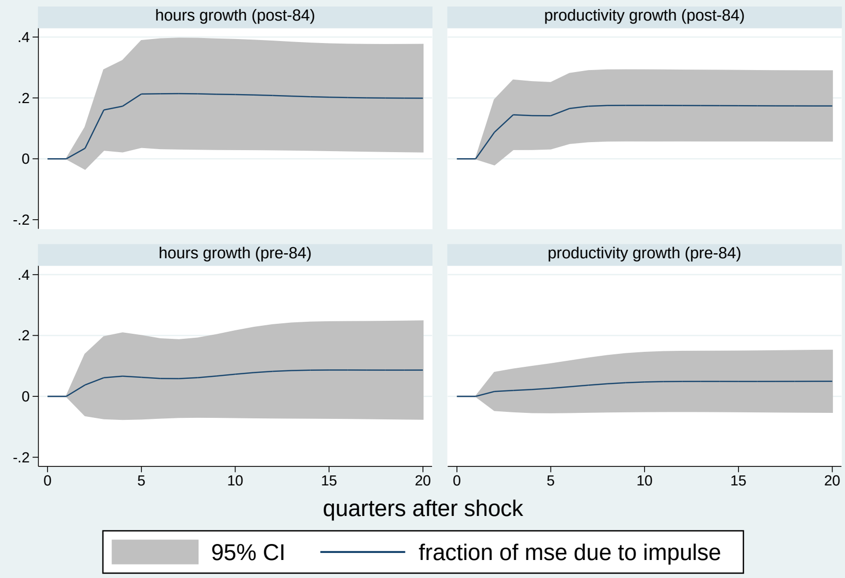

Figure 3. Forecast error variance due to financial shock (pre-84 and post-84)

Finally, we examine the relative contribution of productivity shocks to the forecast error variance of labor productivity during both periods. The left panel of figure 4 shows that after 1984, the contribution of productivity shocks to the variance of labor productivity has declined relative to the pre-84 period (right panel); where the latter panel shows that the contribution of productivity shocks to labor productivity is statistically indistinguishable from 100%.

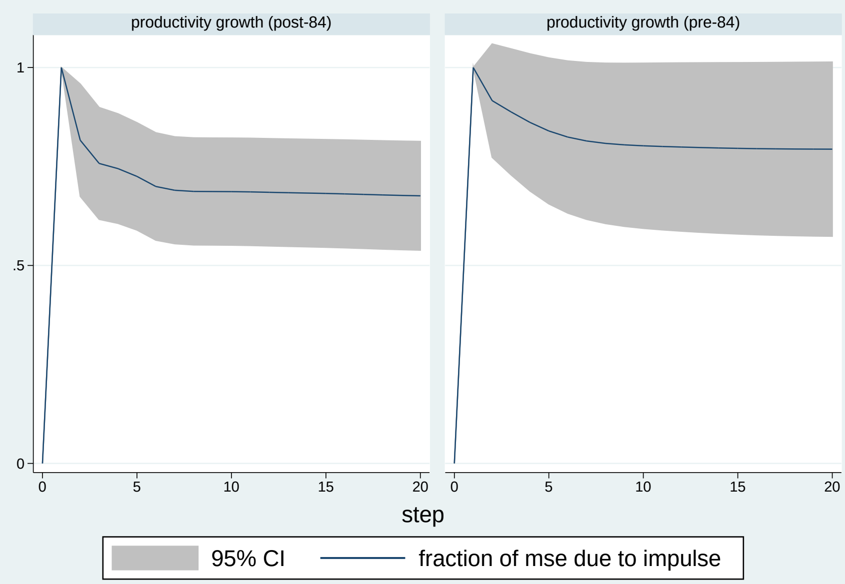

Figure 4. Forecast error variance decomposition due to productivity shock (pre-84 and post-84)

Altogether, the VAR evidence indicates that financial shocks have had a significant impact on both labor productivity and hours worked since the mid-80s. Importantly, we find that the relative contribution of financial shocks to the variability of these key labor market variables has become more important since the mid-80s.

1.2 Structural VAR evidence

We also examine the impact of productivity and financial shocks using a bi-variate structural VAR (SVAR) with long-run restrictions in the spirit of Galí 1999. The endogenous variables are: (1) log-difference of labor productivity; and (2) excess bond premium. I impose as (long-run) identifying restrictions, that the off-diagonal elements of the matrix of structural shocks are zero. This assumption implies productivity shocks do not affect the long-run level of the *ebp*, while financial shocks do not affect long-run productivity growth. Hence, suggestive of no long-run implications between productivity and risk. As in the previous exercise, I divide the data in pre- and post-84 sub-samples.

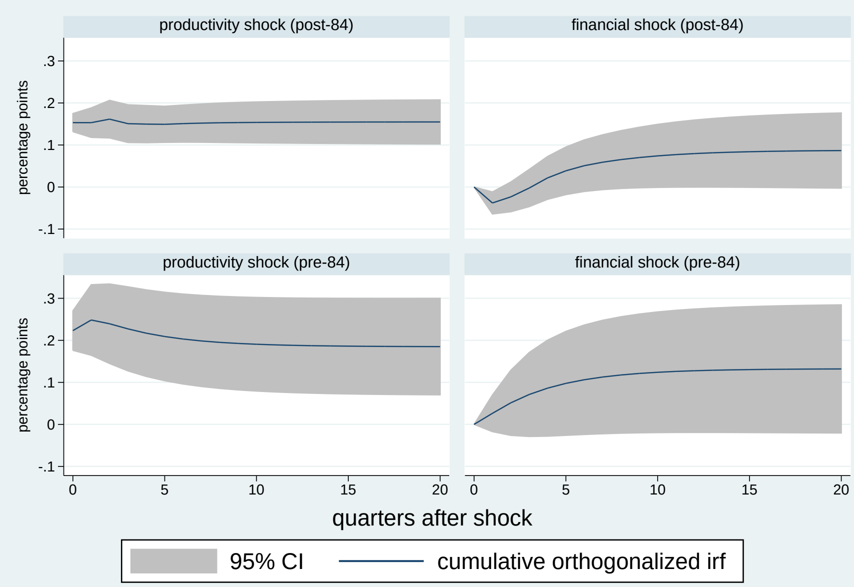

Figure 5. Dynamic responses of labor productivity from SVAR model (pre-84 and post-84)

Figures 5 and 6 show the effect of technology and financial shocks (one-standard deviation each) on labor productivity for the post-84 (upper panel) and pre-84 (lower panel) sub-samples respectively. As expected, the left panel of figure 5 shows that productivity shocks have a positive and significant effect on labor productivity in both sub-samples. More importantly however, in the right panel of figure 5 we find that financial shocks have had a negative and significant effect on labor productivity in the post-84 period, while they had no significant effect on productivity prior to 1984.

To examine the relative importance of financial shocks we look at the forecast error variance decomposition of labor productivity as shown in Figure 6. We find that financial shocks play an important role in explaining the variability of labor productivity in the period following 1984.

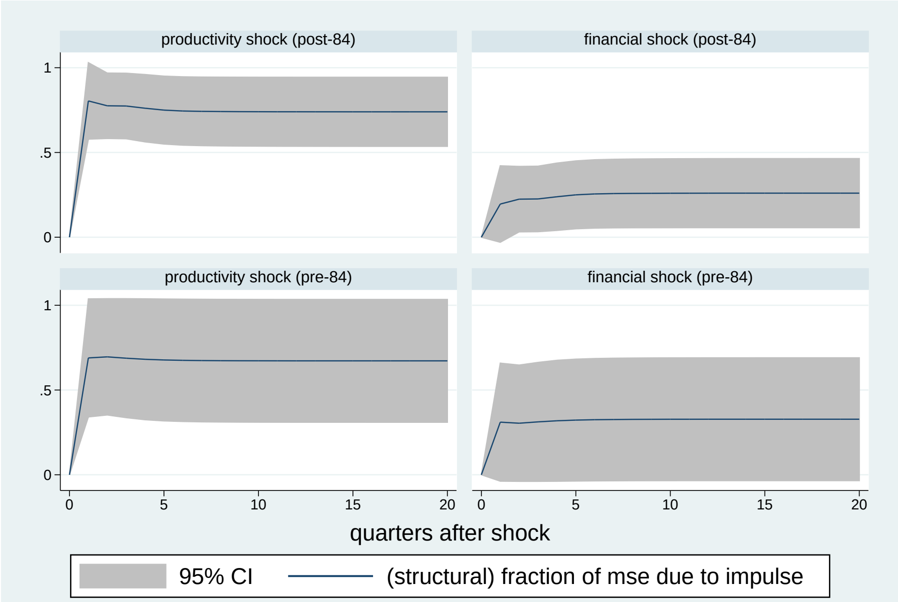

Figure 6. Forecast error variance of labor productivity from SVAR model (pre-84 and post-84)

Altogether, the reduced VAR and SVAR evidence provide support for the notion that financial shocks have become more prominent since the mid-80s.

1.3 Data

The macro series are from St. Louis Fed FRED database and include real GDP, private consumption expenditures, gross private domestic investment, nonfarm business sector hours worked, and the effective (nominal) federal funds rate. Productivity data is real output per capita per hour and per worker from the Bureau of Labor statistics (BLS). The time series cover the period 1947Q1:2010Q3, data is seasonally adjusted at quarterly frequency. The financial variables include debt (Credit Market Instruments) from the Flow of Funds Accounts at the Federal Reserve Board (FRB) and the corporate bond premium (the difference between BAA Moody's corporate bond yield and T-Bill rate yield) from the St. Louis Fed. The excess bond premium data is from Gilchrist and Zakrajsek (2012). The time series cover the period 1973Q1:2010Q3, data is seasonally adjusted at quarterly frequency.

2 Model

The environment is a real business cycle (RBC) model with credit constraints in the spirit of Kiyotaki and Moore 1997. There are two types of agents, unconstrained households and constrained entrepreneurs. The former work and choose how much to consume and save each period. The latter are liquidity constrained and borrow from the former in order to produce and consume.

2.1 Households

Households enjoy consumption and leisure, they derive income from work and accumulate wealth by saving. Their objective function is given by:

$$\max_{c_t^s, n_t} \sum_{t=0}^{\infty} (\beta^s)^t U(c_t^s, n_t)$$

s.t.

$$c_t^s + \frac{b_{t+1}}{R_t} = w_t nt + b_t, \tag{1}$$

with $b_{t+1} \geq -\bar{B}$ for some number $\bar{B}$.

Given prices, w_t the real wage, and R_t the real interest rate, each period the household chooses how much to consume c_t^s and how many hours to work n_t, where β^s denotes the household's discount factor.

Preferences incorporate habit in consumption, a typically used feature to capture the hump-shaped response of output to productivity shocks.

Thus, $U(\cdot) = \left[\frac{(c_t^s - h\, c_{t-1}^s)^{1-\sigma}}{1-\sigma} - \iota \frac{n_t^{1+\phi}}{1+\phi}\right]$, where h is the habit parameter, ι is the (dis)utility weight of labor, and ϕ is the inverse Frisch elasticity of labor supply. The corresponding efficiency conditions are:

$$w_t = -\frac{U_{n_t}}{U_{c_t^s}} \tag{2}$$

$$\frac{1}{E_t\left[m_{t+1}\right]} = R_t \tag{3}$$

Equation (2) is the standard intra-temporal condition that equates the real wage to the marginal rate of substitution, while equation (3) is the standard Euler equation, where the term $E_t[m_{t+1}] = \beta^s E_t\left[\frac{U_{c_{t+1}^s}}{U_{c_t^s}}\right]$ denotes the household's stochastic discount factor.

2.2 Entrepreneurs

Entrepreneurs run firms in the economy and derive utility from consumption c_t^e. They invest i_t in new capital projects and hire labor n_t. Furthermore, entrepreneurs are more impatient than households, $\beta^e < \beta^s$. Hence, the former are borrowing constrained while the latter are not. The entrepreneur's problem is given by:

$$\max_{c_t^e} \sum_{t=0}^{\infty} (\beta^e)^t U(c_t^e)$$

s.t.

$$y_t - n_t\, w_t - b_{t-1} + \frac{b_t}{R_t} = c_t^e + i_t \tag{4}$$

Entrepreneurial production is given by $y_t = z_t\ (u_t\, k_t)^{\alpha}\ n_t^{1-\alpha}$, where k_t and n_t are capital and labor inputs respectively, z_t is technology, and α is the capital share of income. In addition, consistent with a widely accepted extension of the RBC model, I add a capacity utilization u_t margin to production.[1]

As in Jermann and Quadrini 2012, entrepreneurs are liquidity constrained. That is, entrepreneurs require an intra-period loan in order to finance their working capital bills at the beginning of each period and before the realization of revenues. Entrepreneurial liquidity each period is set to $l_t = y_t$, and is subject to a financial friction in the form of a limited enforcement constraint (LEC) given by:

$$\xi_t\, E_t \left[k_{t+1} - \frac{b_{t+1}}{R_t} \right] \geq l_t \tag{5}$$

Equation (5) establishes that entrepreneurial liquidity l_t is tied to a fraction ξ_t of collateral. That is, due to limited enforcement, creditors can only recoup a fraction ξ_t of collateral in case of entrepreneurial default. In addition, capital accumulation follows the law of motion:

$$k_{t+1} = (1 - \delta(u_t))k_t + i_t \tag{6}$$

with the standard regularity condition $\frac{\delta''(u)}{\delta'(u)} u > 0$.

Finally, productivity (z_t) and financial (ξ_t) shocks follow a standard VAR(1) process $\Omega_t = \{z_t, \xi_t\}' = \mathbf{A}\Omega_{t-1} + \epsilon_{\mathbf{t}}$, with $\epsilon_t \sim i.i.d.\ N(0, \Sigma^2)$.

The efficiency conditions that solve the entrepreneur's problem are:

$$y_{n_t} = \frac{w_t}{(1 - q_t)} \tag{7}$$

$$E_t \left[m_{t+1}^e \left(1 - \delta(u_{t+1}) + y_{k_{t+1}} \left(1 - q_{t+1}\right) \right) \right] = 1 - q_t \xi_t \tag{8}$$

$$\frac{1}{E_t \left[m_{t+1}^e \right]} = \frac{R_t}{1 - q_t \xi_t} \tag{9}$$

$$\delta'(u_t) = \frac{y_{k_t}}{u_t} \tag{10}$$

[1]For a theoretical formulation see King and Rebelo (1999). For an empirical basis see Basu, et al. (2004).

where y_{n_t} denotes the marginal product of labor (MPL); the marginal product of capital (MPK) is y_{k_t}; μ_t is the shadow price associated with the limited enforcement constraint (LEC); $U_{c^e_t}$ is the marginal utility of consumption, and $E_t[m^e_{t+1}] \equiv \beta^e E_t\left[\frac{U_{c^e_{t+1}}}{U_{c^e_t}}\right]$ denotes the entrepreneur's stochastic discount factor.

Equation (7) equates the marginal product of labor to the *liquidation-adjusted* real wage $w_t/(1-q_t)$. That is, the cost of labor adjusted by $q_t \equiv \frac{\mu_t}{U_{c^e_t}}$, the shadow price of credit in consumption units. Equation (8) relates the *liquidation-adjusted* value of an additional unit of capital $1-q_t\xi_t$, with its future expected marginal productivity. Equation (9) relates the entrepreneurial stochastic discount factor to the *liquidation-adjusted* interest rate $R_t/(1-q_t\xi_t)$. Last, equation (10) is the optimality condition with respect to capital utilization.

3 Model Analysis

We now proceed to interpret how financial shocks in the model's environment relate to other standard measures of credit conditions. Recall that entrepreneurs however are credit constrained, so the 'effective' rate of return that they face R^k_t is different from households R^k_t, where the former can be interpreted as the credit constrained cost of investment, namely:

$$R^k_t \equiv \frac{1}{E_t\left[m^e_{t+1}\right]} = \frac{R_t}{1-q_t\xi_t} \tag{11}$$

where $E_t[m^e_{t+1}] \equiv \beta^e E_t\left[\frac{U_{c^e_{t+1}}}{U_{c^e_t}}\right]$ denotes the entrepreneur's stochastic discount factor, q_t is the shadow price of credit in consumption units, and ξ_t is the financial shock. Notice that in equilibrium the borrowing constraint binds, so we can interpret

$$E_t[R^k_{t+1} - R_{t+1}] \geq 0$$

as the model implied *credit spread*.
Next, we examine whether the variation in the calibrated model's implied *credit spread* is linked to independent measures of credit conditions for the post-84 period. Namely, i) Moody's BAA corporate bond yield (relative to 10-year treasure bill), ii) the BAA-to-AAA corporate bonds yield, iii) GZ credit spread, and the iv) excess bond premium. The results are summarized in Table 1 below.[2]

[2]The parameter matrix of productivity and financial shocks is drawn from from the post-84 estimates from Jermann and Quadrini 2012. The shock matrix is likely to have different parameter values before this period, therefore I do not provide a set of model results for the period prior to 1984.

post-84					
$\sigma^y = 1.11$	*gz*	*ebp*	*baa2tbill*	*baa2aaa*	*model*
$\frac{\sigma^x}{\sigma^y}$	0.65	0.38	0.46	0.26	0.22
$\rho(x, y)$	-0.32	-0.17	-0.25	-0.45	-0.67
pre-84					
$\sigma^y = 2.33$					
$\frac{\sigma^x}{\sigma^y}$	0.12	0.10	0.27	0.17	< 1
$\rho(x, y)$	-0.56	-0.57	-0.70	-0.71	(-)

Table 1. Cyclical properties of independent measures of credit conditions (x) relative to output (y). Statistics are from HP-filtered data at quarterly frequency with smoothing parameter 1600. Data subsamples are 1984q1:2010q3 (post-84) and 1973q1:1983q4 (pre-84)[3]

In summary, on the empirical side, during the post-84 period credit spreads have become more volatile and less counter-cyclical, which is suggestive of the the notion that credit conditions have become more prominent since the mid-80s. Furthermore, on the theory side, the cyclical behavior of the credit spread that emerges from the model is consistent the the counter-cyclicality and low relative volatility of independent measures of credit conditions.

References

J. Galí. Technology, employment, and the business cycle: Do technology shocks explain aggregate fluctuations? *American Economic Review*, (89(1)):249–71, 1999.

S. Gilchrist and E. Zakrajšek. Credit spreads and business cycle fluctuations. *American Economic Review*, 102(4):1692–1721, 2012.

U. Jermann and V. Quadrini. Macroeconomic effects of financial shocks. *American Economic Review*, 102(1):238–271, 2012.

N. Kiyotaki and J. Moore. Credit cycles. *The Journal of Political Economy*, (105):211–48, 1997.

[3]Data sub-sample for Moody's baa yield relative to 10-year T-bill starts in 1975q1.