(Asset) Pricing the Business Cycle

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Abstract

Asset values of labor and capital govern firms' hiring and investment decisions. The predictive content for economic activity embodied in them is the result of forward-looking optimal behavior. While there are no market prices for these shadow values, this paper derives them using real, aggregate U.S data and structural estimation. Using a LP-IV methodology these time series are shown to be highly useful predictors, parsimoniously encompassing the firm's information and expectations sets. Any aggregate model that features forward-looking firm production may make use of such real asset prices, including DSGE models.

The business cycle is manifested in the cyclical fluctuations of GDP and its main input factors – employment and capital; the afore-going real asset values are the "asset prices" of these quantities.

The paper characterizes them, finding some non-obvious features: labor and capital asset values are weakly correlated, driven by different shocks, even though the decision variables, investment and vacancy rates, are highly correlated; labor values, which are more volatile, have stronger effects on both decision variables relative to capital values; and labor values are pro-cyclical, while capital values, where the price of capital plays a major role, are counter-cyclical.

Both asset values are shown to have very good performance in predicting GDP, as well as investment and vacancy creation rates, over the cycle.

Key words: Business cycles, production-based real asset pricing, labor value, capital value, optimal investment, optimal hiring, GMM, IV-local projections, ROC analysis, predictors.

JEL codes: E22, E23, E24, E32.

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(Asset) Pricing the Business Cycle[1]

1 Introduction

The paper estimates the asset values of capital and of labor in the aggregate U.S. economy, thereby obtaining time series of important but unobserved asset prices. The paper finds that these asset values have significant predictive value, and can therefore serve as sufficient statistics and predictors. The underlying logic is the following. When firms hire workers and invest in capital, they take into account current costs and the expected, present discounted values of labor and of capital, equating them at the margin. Hence these activities are essentially investment activities. The asset values in question are not market prices but rather shadow values, and the paper estimates them using aggregate, real U.S. data. Estimation makes use of the existence of frictions in investment and in hiring, focusing on the ensuing dynamic optimization problem, with emphasis on joint optimality. This is a production-based, real, asset-pricing type of empirical analysis, with three relevant shadow values expressing inter-related firm, capital, and labor asset values. The business cycle is manifested in the cyclical fluctuations of GDP and its main input factors – employment and capital; the afore-going asset values are the "asset prices" of these quantities, hence the title of this paper.

While using Tobin's q terminology, the analysis does not rely on financial market data or firm price data.[2] The idea here is to structurally estimate the shadow values, using data on real variables, such as GDP, wages, relative prices, hiring, and investment. Subsequent to estimation, I use a Local Projections – Instrumental Variables (LP-IV) methodology, based on Jordà (2005) and following Jordà, Schularick, and Taylor (2015, 2019). This serves the empirical exploration of asset values as predictors, including assessing their performance relative to other predictors, and their cyclical behavior. The LP-IV analysis makes use of three technology-related shocks included in the model – TFP, investment-specific, and worker matching.

Structural estimation yields estimates of hiring and investment frictions that are very moderate, hence the results here do not imply unreasonably large frictions. The interaction of hiring and investment frictions proves to be important for model fit. Standard specifications, often used in the Tobin's q and in the labor search and matching literatures, are shown to be rejected by the data.

The empirical work based on the derived asset values shows that these values are of substantive use. It characterizes them, finding some non-obvious features: labor and capital asset values are weakly correlated, driven by different shocks, even though the decision variables, investment and vacancy rates, are highly correlated; labor values, which are more volatile, have stronger effects on both decision variables relative to

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[2] See Merz and Yashiv (2007) for work using financial data in a related context.

capital values; and labor values are pro-cyclical, while capital values, where the price of capital plays a major role, are counter-cyclical.

Their use lies in the fact that both asset values have very good performance in predicting GDP, as well as investment and vacancy creation rates, over the cycle. Labor asset values have a somewhat longer duration effect and are also somewhat better predictors of recessions. The implication is that asset values can serve as sufficient statistics and as predictors, capturing the information and expectations set of the firms. Any aggregate model that features forward-looking firm production may make use of such real asset prices.

Given that the data used here to construct asset values do not include financial markets data, they are not subject to distortions in these markets, such as asset price bubbles, noise trading, short run misvaluations, etc. While the analysis does not make use of financial data, it is consistent with movements in financial asset prices, in particular stock prices.

The paper proceeds as follows. Section 2 presents the relevant background literature. Section 3 delineates the model and the relations to be examined empirically. Section 4 presents structural estimation, deriving time series for the shadow asset values and quantifying the frictions involved. Using the estimation results, Section 5 explores firms' optimal behavior and its determinants, presenting the second moments of asset values and the elasticities of the decision variables with respect to them. Section 6 introduces the LP-IV methodology and discusses the use of asset values as predictors. Employing this methodology, Section 7 studies the predictive performance of capital and labor asset values and their cyclical behavior. Section 8 concludes. Formal derivations and data details are relegated to appendices.

2 Literature

I briefly review key papers within a very large literature that have direct bearing on the analysis undertaken here.[3]

[3] The model formulation used here derives from an important early literature on adjustment costs of factor inputs. Key papers include Lucas (1967) and Mortensen (1973), who derived firm optimal behavior with convex adjustment costs for n factors of production. Lucas and Prescott (1971) embedded these convex adjustment costs in stochastic industry equilibrium. Nadiri and Rosen (1969) considered interrelated factor demand functions for labor and capital with adjustment costs. In a related strand of literature, the seminal papers of Tobin (1969) and Tobin and Brainard (1968) introduced the concept of q. Tobin (1981) posited that investment is a function of q^K (formally defined below, in the next section), noting that "the deviations of q^K from 1 represent real costs of adjustment, including positive or negative rents, incurred by investing firms in changing the size of their installed capital." (p.22) A formalization of the q concept within the latter set of models was offered by Hayashi (1982). An important early empirical implementation for both capital and labor is Shapiro (1986).

2.1 Hiring and Investment Frictions

The paper places emphasis on hiring frictions, investment frictions, and their interactions. It features a costs function, which arguments include the vacancy rate, hiring rates, and the investment rate. I briefly discuss the papers which provide a foundation for its formulation. More broadly, Yashiv (2016) and Faccini and Yashiv (2019) review the hiring frictions literature and Campbell (2018, Chapter 7) reviews the relevant investment frictions literature.

Hiring frictions. While hiring frictions have been key ingredients in the search and matching literature, there are few empirical studies of them using micro data. Recent among those few, aiming to quantify them and study their composition, are the empirical studies by Blatter et al (2016), Mühlemann and Leiser (2018), and Faccini and Yashiv (2019, Section 3). Manning (2011) offers a review of some earlier micro-based studies. The emerging picture is that of convex costs placed mainly on training, with a much more limited role for costs related to vacancies. In the model below I use a costs function allowing for both vacancy and training costs with different weights (which are estimated).

I make a distinction between costs incurred when hiring from other employment (job to job movements) and when hiring from non-employment. As the big part of costs are training costs, these may well differ across these worker flows. An example is provided by a micro study of a large hospital system. Bartel, Beaulieu, Phibbs, and Stone (2014) find that the arrival of a new nurse is associated with lowered productivity, but that this effect is significant only if the nurse is hired externally.

Investment frictions. Campbell (2018, Chapter 7) discusses these frictions in the context of production-based asset pricing models. His discussion points to a convex specification of the type considered here (see his equation 7.26). He points to productivity shocks and to investment specific shocks, which feature in the model below. For an up-to-date discussion of frontier estimation methodologies, firm data used, as well as results of the estimation of key parameters, see Bazdresch, Kahn, and Whited (2018).

Interactions. An important ingredient in the model below is the interaction between investment and hiring costs. A recent theoretical and empirical literature has given foundations to these interaction terms. This literature looks at the connections between investment in capital, the hiring of workers, and organizational and management changes. A general discussion and overview of this line of research is offered by Ichniowsky and Shaw (2013) and by Lazear and Oyer (2013). Consider as an example the case of valve manufacturing. Bartel, Ichniowski and Shaw (2007) study the effects of new information technologies (IT) on productivity using data on plants in this narrowly defined industry. Their empirical analysis reveals, inter alia, that adoption of new IT-enhanced capital equipment coincides with increases in the skill requirements of machine operators, notably technical and problem-solving skills, and with the adoption of new human resource practices to support these skills. They show how investment in capital equipment has a variety of effects on hiring and on training.

Functional form. In the empirical analysis below I use a convex cost function. While non-convexities were found to be significant at the micro level (plant, establishment, or firm), a number of papers have given empirical support for the use of a convex function in the aggregate, showing that such a formulation is appropriate at the macroeconomic level. Thus, Thomas (2002) and Kahn and Thomas (2008, see in particular their discussion on pages 417-421) study a dynamic, stochastic, general equilibrium model with nonconvex capital adjustment costs at the micro level. One key idea which emerges from their analysis is that there are smoothing effects that result from equilibrium price changes.

2.2 Previous Work

In previous work I have used a similar modelling framework but explored different empirical issues. In Merz and Yashiv (2007) the focus was on production-based asset pricing with stock market data. We investigated the links between the financial and labor markets, using a production-based model for firms' market value following Cochrane (1991) and Jermann (1998).[4] We inserted labor and capital adjustment costs into the canonical model and showed that this framework can account well for the behavior of U.S. stock prices. In Yashiv (2016) I decomposed the future determinants of capital and job values and found that future returns play a dominant role in determining capital and job values.

The one point of limited overlap of the current paper with the two cited papers (Merz and Yashiv (2007) and Yashiv (2016)) is structural estimation of the firms' optimality equations. In the current paper the sample period is updated and enlarged and the specification estimated is significantly wider, i.e., it nests the previous ones as special cases. The afore-cited papers, however, did not undertake the empirical work reported here.

3 The Model

The model formulates optimal hiring and investment decisions in the presence of frictions and shocks. The model is a partial equilibrium model, intended to avoid potential misspecifications in other parts of the macroeconomy. I include a discussion of important special cases, which are prevalent in the capital and labor literatures.

3.1 Firm Optimization

Firms use physical capital (k_t) and labor (n_t) as inputs in order to produce output goods y_t according to a constant-returns-to-scale production function f with TFP denoted by z_t:

$$y_t = f(z_t, n_t, k_t), \tag{1}$$

TFP follows the process:

[4] See also the more recent contributions of Cochrane (2007, 2017).

$$\ln z_t = \kappa_1 + \ln z_{t-1} + \varepsilon_t^f \tag{2}$$

where ε_t^f is a shock and κ_1 a parameter.

Once a new worker is hired, the firm pays a per-period wage w_t. Firms make investment (i_t) and vacancy (v_t) decisions, subject to frictions, spelled out below. I represent these costs by a function $g[i_t, k_t, v_t, n_t]$ which is convex in the firm's decision variables (i_t, v_t) and exhibits constant returns-to-scale, allowing hiring costs and investment costs to interact.

In every period t, the capital stock depreciates at the rate δ_t and is augmented by new investment i_t. Similarly, workers separate at the rate ψ_t and the employment stock is augmented by new hires $q_t v_t = h_t$. The laws of motion are:

$$k_{t+1} = (1-\delta_t)k_t + i_t, \quad 0 \leq \delta_t \leq 1. \tag{3}$$

$$n_{t+1} = (1-\psi_t)n_t + q_t v_t, \quad 0 \leq \psi_t \leq 1 \tag{4}$$

The vacancy filling rate q_t reflects labor market conditions and embodies a matching shock μ_t following the AR1 process:

$$\ln \mu_t = \kappa_2 + \rho_\mu \ln \mu_{t-1} + \varepsilon_t^\mu \tag{5}$$

where ε_t^μ is a matching shock and κ_2, ρ_μ are parameters.

The representative firm chooses sequences of i_t and v_t in order to maximize its profits as follows:

$$\max_{\{i_{t+j}, v_{t+j}\}} E_t \sum_{j=0}^{\infty} \left(\prod_{i=0}^{j} \rho_{t+i} \right) (1-\tau_{t+j}) \left(\begin{array}{c} f(z_{t+j}, n_{t+j}, k_{t+j}) - g\left(i_{t+j}, k_{t+j}, v_{t+j}, n_{t+j}\right) \\ -w_{t+j}n_{t+j} - \left(1-\chi_{t+j} - \tau_{t+j}D_{t+j}\right) \widetilde{p}_{t+j}^I \; i_{t+j} \end{array} \right) \tag{6}$$

subject to the constraints (3) and (4), where τ_t is the corporate income tax rate, χ_t the investment tax credit, D_t the present discounted value of capital depreciation allowances, $\tilde{p}_t^I$ the real pre-tax price of investment goods, and ρ_{t+j} is a time-varying discount factor. In line with the investment technology literature, $\tilde{p}_t^I$ is driven by an unanticipated IST shock as follows:

$$\begin{aligned} \widetilde{p}_t^I &\equiv \frac{1}{\Theta_t} \\ \ln \Theta_t &= \kappa_3 + \rho_\Theta \ln \Theta_{t-1} + \varepsilon_t^I \end{aligned} \tag{7}$$

where ε_t^I is the shock and κ_3, ρ_Θ are parameters.

The firm takes the shocks and the paths of the variables $q_t, w_t, \widetilde{p}_t^I, \psi_t, , \delta_t, \tau_t$ and ρ_t as given. The Lagrange multipliers associated with the two constraints are denoted Q_t^K and Q_t^N, respectively. I shall use the term capital value for the former, and labor value for the latter.

The first-order conditions for dynamic optimality can be written as follows:[5]

$$Q_t^K = (1-\tau_t)\left(g_{i_t} + p_t^I\right) = E_t\left[\rho_{t+1}(1-\tau_{t+1})\left[\begin{array}{c} f_{k_{t+1}} - g_{k_{t+1}} \\ +(1-\delta_{t+1})(g_{i_{t+1}} + p_{t+1}^I) \end{array}\right]\right] \tag{8}$$

$$Q_t^N = (1-\tau_t)\frac{g_{v_t}}{q_t} = E_t\left[\rho_{t+1}(1-\tau_{t+1})\left[\begin{array}{c} f_{n_{t+1}} - g_{n_{t+1}} - w_{t+1} \\ +(1-\psi_{t+1})\frac{g_{v_{t+1}}}{q_{t+1}} \end{array}\right]\right] \tag{9}$$

The capital value (Q_t^K) is the present value of expected marginal productivities, adjusted for taxes and depreciation; the labor value (Q_t^N) is the present value of the expected profit flows from the marginal worker adjusted for taxes and separation rates.

3.2 Investment and Hiring Costs

The costs function g, captures the frictions in the hiring and investment processes. Hiring costs include costs of advertising, screening and testing, matching frictions, training costs, and more. Thus, they pertain to vacancy posting, actual hires from non-employment, and hires from employment (job to job movements). Investment involves capital installation costs, implementation costs, learning the use of new equipment, and implementing new organizational structures within the firm.[6] In sum, g captures all the frictions involved in getting workers to work and capital to operate in production.

3.2.1 Hiring and Separation Flows[7]

Firms hire from non-employment (h_t^1) and from other firms (h_t^2). Each period, the worker's effective units of labor (normally 1 per person) depreciate to 0, in the current firm, with some exogenous probability ψ_t. Thus, the match suffers an irreversible idiosyncratic shock that makes it no longer viable. The worker may be reallocated, with a probability of ψ_t^2, to a new firm where his/her productivity is (temporarily) restored to 1. Those who are not reallocated join unemployment with probability $\psi_t^1 = \psi_t - \psi_t^2$. So the fraction ψ_t^2 that enters job to job flows depends on the endogenous hiring flow h_t^2. The firm decides how many vacancies v_t to open and, given job filling rates (q_t^1, q_t^2), will get to hire from the pre-existing non-employed and from the pool of dissolved matches.

Employment dynamics are thus given by:

$$\begin{aligned} n_{t+1} &= (1-\psi_t^1-\psi_t^2)n_t + h_t^1 + h_t^2 \\ &= (1-\psi_t)n_t + h_t, \quad 0 \le \psi_t \le 1 \\ h_t^2 &= \psi_t^2 n_t \end{aligned} \tag{10}$$

[5]where I use the real after-tax price of investment goods, given by:

$$p_{t+j}^I = \frac{1-\chi_{t+j} - \tau_{t+j}D_{t+j}}{1-\tau_{t+j}}\,\widetilde{p}_{t+j}^I$$

[6]See Alexopoulos and Tombe (2012).

[7]I am indebted to Giuseppe Moscarini for very useful suggestions to this sub-section.

The job-filling rates satisfy:

$$q_t^1 = \frac{h_t^1}{v_t}; \quad q_t^2 = \frac{h_t^2}{v_t}; \quad q_t = q_t^1 + q_t^2$$

3.2.2 Functional Form of the Costs Function

The parametric form I use is the following, generalized convex function. In the empirical work below, all of its parameters are estimated.

$$g(\cdot) = \begin{bmatrix} \frac{e_1}{\eta_1}(\frac{i_t}{k_t})^{\eta_1} \\ +\frac{e_2}{\eta_2}\left[\frac{(1-\lambda_1-\lambda_2)v_t+\lambda_1 q_t^1 v_t+\lambda_2 q_t^2 v_t}{n_t}\right]^{\eta_2} \\ +\frac{e_{31}}{\eta_{31}}\left(\frac{i_t}{k_t}\frac{q_t^1 v_t}{n_t}\right)^{\eta_{31}} + \frac{e_{32}}{\eta_{32}}\left(\frac{i_t}{k_t}\frac{q_t^2 v_t}{n_t}\right)^{\eta_{32}} \end{bmatrix} f(z_t, n_t, k_t). \tag{11}$$

This is a convex function in the rates of activity – investment ($\frac{i_t}{k_t}$) and recruiting ($\frac{(1-\lambda_1-\lambda_2)v_t+\lambda_1 h_t^1+\lambda_2 h_t^2}{n_t}$). The function is linearly homogenous in its arguments i, k, v, n. The parameters e_l, $l = 1, 2, 31, 32$ express scale, and the parameters $\eta_1, \eta_2, \eta_{31}, \eta_{32}$ express the convexity of the costs function. λ_1 is the weight in the cost function assigned to hiring from non-employment ($\frac{q_t^1 v_t}{n_t}$), λ_2 is the weight assigned to hiring from other firms ($\frac{q_t^2 v_t}{n_t}$), and $(1 - \lambda_1 - \lambda_2)$ is the weight assigned to vacancy ($\frac{v_t}{n_t}$) costs. The weights λ_1 and λ_2 are thus related to the training and production disruption aspects, while the complementary weight is related to the vacancy creation aspect. The terms $\frac{e_{31}}{\eta_{31}}\left(\frac{i_t}{k_t}\frac{q_t^1 v_t}{n_t}\right)^{\eta_{31}}$ and $\frac{e_{32}}{\eta_{32}}\left(\frac{i_t}{k_t}\frac{q_t^2 v_t}{n_t}\right)^{\eta_{32}}$ express the interaction of investment and hiring costs. They allow for a different interaction for hires from non-employment (h_t^1) and from other firms (h_t^2). The function used postulates that costs are proportional to output.

This functional formulation may be justified as follows (drawing on Garibaldi and Moen (2009)): suppose each worker i makes a recruiting and training effort h_i; as this is to be modelled as a convex function, it is optimal to spread out the efforts equally across workers so $h_i = \frac{h}{n}$; formulating the costs as a function of these efforts and putting them in terms of output per worker, one gets $c\left(\frac{h}{n}\right)\frac{f}{n}$; as n workers do it, the aggregate cost function is given by $c\left(\frac{h}{n}\right) f$.

3.3 Important Special Cases

Beyond the general model spelled out above, I examine important special cases, widely-used in the capital and labor literatures.

a. Relying on the seminal contributions of Tobin (1969) and Hayashi (1982), this approach assumes no adjustment costs for the other factor of production. In the current case, this is convex costs of investment in capital (labor), with no hiring (investment) costs. Typically quadratic costs are posited. Hence in the former case this has $e_2 = e_{31} = e_{32} = 0$ and $\eta_1 = 2$ and in the latter case $e_1 = e_{31} = e_{32} = 0$ and $\eta_2 = 2$.

b. The standard search and matching model – see Pissarides (2000) for an overview – does not consider investment when formulating costs and refers to linear vacancy costs. The specification is thus $\frac{e_2}{q_t}\frac{f_t}{n_t}v_t$ whereby the cost is proportional to labor productivity $\frac{f_t}{n_t}$ and depends on the average duration of the vacancy $\frac{1}{q_t}$. In terms of the above model it has $e_1 = e_{31} = e_{32} = 0, \lambda_1 = \lambda_2 = 0$ and $\eta_2 = 1$.

3.4 Asset Values

I formulate the relevant asset values inherent in the analysis. Appendix A shows the full derivation, yielding (in stationary terms, divided by GDP):

$$\frac{Q_t}{f_t} = \frac{k_{t+1}}{k_t}\frac{Q_t^K}{\frac{f_t}{k_t}} + \frac{n_{t+1}}{n_t}\frac{Q_t^N}{\frac{f_t}{n_t}} \tag{12}$$

where aggregate firm value is denoted by Q_t.

The terms on the RHS of (12) are given by the following expressions, in terms of output per unit of input (using equations (8) –(9)) :

$$\frac{Q_t^K}{\frac{f_t}{k_t}} = (1-\tau_t)\left(\frac{g_{i_t}}{\frac{f_t}{k_t}} + \frac{p_t^I}{\frac{f_t}{k_t}}\right) \tag{13}$$

$$\frac{Q_t^N}{\frac{f_t}{n_t}} = (1-\tau_t)\frac{\frac{g_{v_t}}{q_t}}{\frac{f_t}{n_t}} \tag{14}$$

The analysis below focuses on the last two expressions.

4 Estimating Optimal Behavior and Deriving Asset Values

The first stage of the empirical work is to determine whether the model fits the data, how does it fare relative to standard specifications, and to derive time series for the different asset values (formulated in equations (12) – (14)), which are unobserved. This is done through structural estimation of the afore-going optimality equations of the firm.

4.1 Data and Methodology

The data are quarterly and pertain to the aggregate private sector of the U.S. economy. For a large part of the empirical work reported below the sample period is 1994-2016. The start date of 1994 is due to the lack of availability of job to job worker flows (h_t^2) data prior to that. For another part of the empirical work, the sample covers 1976-2016.

The 1976 start is due to the availability of credible monthly CPS data, from which the gross hiring flows from non-employment (h_t^1) series is derived. This longer sample period covers five NBER-dated recessions, and both sample periods include the Great Recession (2007-2009) and its aftermath. Appendix B elaborates on sources and on data construction.

I structurally estimate the firms' first-order conditions – equation (8) and equation (14) – jointly, using Hansen's (1982) generalized method of moments (GMM). In what follows I outline the methodology and the alternative specifications used. A much more detailed exposition is provided in Appendix C.

For the production function I use a standard Cobb-Douglas formulation, with a productivity shock $\exp(z_t)$:

$$f(z_t, n_t, k_t) = \exp(z_t) n_t{}^{\alpha} k_t^{1-\alpha},\ 0 < \alpha < 1. \tag{15}$$

Replacing expected values in these equations by actual ones and expectational errors ($j_t^{k,n}$), the estimation equations are given by (estimation is undertaken after dividing the investment equation by $\frac{f_t}{k_t}$ and the vacancy equation by $\frac{f_t}{n_t}$ to induce stationarity):

$$(1-\tau_t)\left(g_{i_t} + p_t^I\right) = \rho_{t+1}\left(1-\tau_{t+1}\right)\left[\begin{array}{c} f_{k_{t+1}} - g_{k_{t+1}} \\ +(1-\delta_{t+1})(g_{i_{t+1}} + p_{t+1}^I) \end{array}\right] + j_t^k \tag{16}$$

$$(1-\tau_t)\frac{g_{v_t}}{q_t} = \rho_{t+1}\left(1-\tau_{t+1}\right)\left[\begin{array}{c} f_{n_{t+1}} - g_{n_{t+1}} - w_{t+1} \\ +(1-\psi_{t+1})\frac{g_{v_{t+1}}}{q_{t+1}} \end{array}\right] + j_t^n \tag{17}$$

The moment conditions estimated are those obtained under rational expectations i.e., $E(\mathbf{Z}_t \otimes j_t) = 0$ where $\mathbf{Z}_t$ is the vector of instruments. The instrument set includes 8 lags of the key variables – the hiring rate ($\frac{h_t}{n_t}$) and the investment rate ($\frac{i_t}{k_t}$) for both equations; the rate of growth of output per unit of capital ($\frac{f_t}{k_t}$) and the depreciation rate (δ_t) for equation (16); and the labor share ($\frac{w_t n_t}{f_t}$) and rate of separation (ψ_t) for equation (17). I report the J-statistic χ^2 test of the over-identifying restrictions. It should be noted that no restriction is placed on any parameter estimate.

4.2 Estimation Results

Table 1 presents GMM estimates of equations (16) and (17).

Table 1

Consider panel a. Row (a) estimates all eleven parameters. Eight of these are not precisely estimated, but suggest a quadratic g function with linear interactions, provide for a very reasonable estimate of the production function, and place the most weight in hiring costs on those associated with the h_t^1 gross flows from non-employment. The J-statistic result does not reject the null hypothesis.

Row (b) restricts four of the parameters of the costs function to the point estimates presented in row (a), yielding a quadratic function ($\eta_1 = \eta_2 = 2$) with linear interactions ($\eta_{31} = \eta_{32} = 1$). Here the seven free parameters are precisely estimated, the estimate of α is around the conventional estimate of 0.66, and the J-statistic again has a high p-value. The point estimates are close to those of the unrestricted row (a).

Row (c) takes up the same specification as row (b) but ignores job to job flows, i.e., sets $\lambda_2 = e_{32} = 0$ and $h_t^2 = \psi_t^2 = 0$. This allows for the use of a longer data sample – 1976:1-2016:4, with 168 quarterly observations. It, too, yields a J-statistic with a high p-value, and is, for the most part, precisely estimated. Evidently the estimates are not the same as those of row (b), but there is considerable affinity.

The three rows yield similar results in terms of the implied costs as reported below. The main take-aways from these estimates are: the costs function features quadratic costs with linear interactions; the latter feature negative coefficients ($e_{31}, e_{32} < 0$), implying complementarity between hiring and investment; and the bigger weight of recruitment costs is assigned to actual hires from non-employment, i.e. λ_1 at around 0.65.

Now consider panel b relating to the standard specifications in the literature. Row (a) follows the standard Tobin's q for capital model. It has quadratic investment costs, with no role for labor. There is no rejection of the model, but this specification implies high marginal investment costs, discussed below. This is reminiscent of the results in much of the literature on Tobin'q models for investment

Row (b) posits the same "standard Tobin's q model" but this time for labor, ignoring capital. Most parameters are imprecisely estimated and the J statistic rejects the null.

Row (c) reports the results of the standard (Pissarides-type) search and matching model formulation with linear vacancy costs and no other arguments. The J statistic implies rejection and the estimates imply high total costs, as discussed below.

Hence standard specifications are rejected or deemed implausible. In the next sections, I take row (b) of panel a as the preferred estimates.

Table 2 shows the mean and second moments of the estimated asset values derived from the GMM estimates.

Table 2

Total costs. Total costs out of GDP ($\frac{g_t}{f_t}$) are estimated to be 3.2-3.3% across rows (a)-(c) of panel a with little variation. In terms of panel b, the two Tobin's q specifications with one factor only indicate 1.1% for the capital case and 2.5% for the labor case; jointly this is somewhat higher than the panel a estimates. The standard search and matching model estimates, however, imply more than double the costs, 6.8% of GDP, with a big increase in their volatility.

Marginal investment costs. These are expressed in terms of the percentage out of the marginal capital unit price, $\frac{g_{i_t}}{p_t^I}$. The results of rows (a) – (c) in panel a point to 2.4%-3.4%, i.e. for every dollar spent on the marginal unit of capital, these costs add 2.4–3.4 cents. These results correspond to micro papers in the investment q-literature which reported low costs. The one relevant result in panel b, row (a), Tobin's q for capital, yields a much larger estimate, 7.5%, reflecting a long-running problem with this widely-used specification.

Marginal hiring costs. These are expressed in terms equivalent to quarterly wages, $\frac{g v_t}{q_t w_t}$, and are equal to the tax adjusted labor value to wage ratio, $\frac{\frac{Q_t^N}{(1-\tau_t)}}{w_t}$. The results of rows (a) – (c) in panel a point to the equivalent of 50%-65% of quarterly wages, or the equivalent of 6.4 to 8.4 weeks of wages, for marginal costs.

One finding here relates to a recurrent question in research on business cycles with labor market frictions (see, for example, Christiano, Trabandt, and Walentin (2011 pp. 2038-2039) and Faccini and Yashiv (2019, Sections 2.1, 3, and 5)) – what is the share of vacancy costs vs post-match costs (training, for example) in firms hiring costs? The importance of this question stems from the fact that vacancy costs relate to labor market conditions, while training costs relate to internal firm conditions. The results here indicate that the latter are by far dominant: $\lambda_1 + \lambda_2$ is estimated at about 0.85, so vacancy costs are only about 15% of total hiring costs. This is fully consistent with the results of the recent micro-based studies, discussed in Section 2 above.

The conclusions from this discussion are that hiring and investment costs in rows (a)-(c) of panel a are very moderate. Hence, the analysis below does not rely on excessive or implausible costs, an issue that was the drawback of the relevant literatures for decades The afore-going analysis has shown that the model fits U.S. data well, in a period of over four decades, including the decade of the Great Recession and its aftermath. Prevalent models, in the Tobin's q and search and matching traditions, do not fit, as they ignore cross effects between investment and hiring frictions. The interaction estimates imply complementarity in investment and hiring activities. The fit relies on very moderate estimates of the frictions. Time series for the shadow asset values are derived and used extensively below.

5 Optimal Firm Behavior and Asset Values

Using the GMM estimates (see Tables 1 and 2), the relations of the estimated asset values, as well as of the relative price of investment, to the decision variables can now be examined. Appendix D provides the full derivation of what follows.

The decision rules implied by equations (16) and (17) are as follows, using the preferred parameter estimates. Optimal investment is given by:

$$\frac{i_t}{k_t} = \frac{1}{e_1 e_2 \Lambda_t^2 - \Omega_t^2} \left[e_2 \Lambda_t^2 \left(\frac{Q_t^K}{(1-\tau_t)\frac{f_t}{k_t}} - \frac{p_t^I}{\frac{f_t}{k_t}} \right) - q_t \Omega_t \frac{Q_t^N}{(1-\tau_t)\frac{f_t}{n_t}} \right] \tag{18}$$

where:

$$\begin{aligned} \Lambda_t &\equiv (1-\lambda_1-\lambda_2) + \lambda_1 q_t^1 + \lambda_2 q_t^2 > 0 \\ \Omega_t &\equiv e_{31} q_t^1 + e_{32} q_t^2 < 0 \end{aligned}$$

Capital asset values are given by:

$$\frac{Q_t^K}{(1-\tau_t)\frac{f_t}{k_t}} = \left(\left[e_1(\frac{i_t}{k_t}) + e_{31}\left(\frac{q_t^1 v_t}{n_t}\right) + e_{32}\left(\frac{q_t^2 v_t}{n_t}\right)\right] + \frac{p_t^I}{\frac{f_t}{k_t}}\right) \tag{19}$$

Equation (18) implies that the investment rate is a positive function of asset values and of the corporate tax rate and a negative function of the price of investment. The intuition is that as the present value of the marginal investment unit or of the marginal hire rise, the firm invests more. The positive relationship with the current tax rate is explained by the fact that corporate taxes are reduced by costs being expensed, so, ceteris paribus, without changes in future rates, the current tax rate rise gives an incentive to invest more now.[8]As the price of investment rises, the rate of investment falls.

Optimal vacancy creation is given by:

$$\frac{v_t}{n_t} = \frac{1}{e_1 e_2 \Lambda_t^2 - \Omega_t^2}\left[e_1 q_t \frac{Q_t^N}{(1-\tau_t)\frac{f_t}{n_t}} - \Omega_t\left(\frac{Q_t^K}{(1-\tau_t)\frac{f_t}{k_t}} - \frac{p_t^I}{\frac{f_t}{k_t}}\right)\right] \tag{20}$$

Labor asset values are given by:

$$\frac{Q_t^N}{(1-\tau_t)\frac{f_t}{n_t}} = \frac{\left[\begin{array}{c} e_2\frac{v_t}{n_t}\left[(1-\lambda_1-\lambda_2)+\lambda_1 q_t^1+\lambda_2 q_t^2\right]^2 \\ +e_{31}q_t^1\left(\frac{i_t}{k_t}\right)+e_{32}q_t^2\left(\frac{i_t}{k_t}\right)\end{array}\right]}{q_t} \tag{21}$$

Likewise, the vacancy rate is unmabiguously a positive function of the asset values and of the corporate tax rate, for reasons similar to the ones presented above.

The effects of the two job filling rates (q_t^1, q_t^2),[9] which reflect two sets of labor market conditions,[10] are ambiguous: on the one hand they operate to raise investment and vacancy rates when they rise as the expected present value on the RHS of equation (18) rises.[11] On the other hand the operate to lower them, as costs on hiring flows $(\frac{q_t^1 v_t}{n_t}, \frac{q_t^2 v_t}{n_t})$ rise, expressed through the $e_1 e_2 \Lambda_t^2$ term.

Panel a of Table 3 reports the second moments of the tax-adjusted asset values, expressed in equations (19) and (21), of $\frac{p_t^I}{\frac{f_t}{k_t}}$, of the decision variables, the rates of investment and vacancies, and of the change in GDP, all in logs. Note that the relative price of capital constitutes a large part of capital asset values.

Table 3

[8]Note, too, that τ_t includes χ_t the investment tax credit, and D_t the present discounted value of capital depreciation allowances,

[9]The explicit formulation is derived in Appendix D.

[10]The rate q_t^1 pertains to worker flows from non-employment while the rate q_t^2 pertains to worker flows from other employment.

[11]Note that $\Omega_t < 0$, so last term on the RHS of (18) and of (20) is positive.

Panel a of the table shows the following.

First, labor asset values $(\frac{Q_t^N}{(1-\tau_t)\frac{f_t}{n_t}})$ and vacancy rates $(\frac{v_t}{n_t})$ are more volatile than capital asset values $(\frac{Q_t^K}{(1-\tau_t)\frac{f_t}{k_t}})$ and the investment rate $(\frac{i_t}{k_t})$, respectively. All of them are considerably more volatile than GDP changes.

Second, while the vacancy rate and the investment rate are highly and positively correlated (0.88), the correlation between the two asset values is negative and very weak (-0.13). How to interpret this result? Note that this correlation is not the partial or marginal effect of one variable on the other. Recall that each asset value captures the expected discounted value of future productivities – those of capital and those of labor, net of wages, and these differ. Indeed, Section 7 below shows that they are driven by different shocks. More technically, while both asset values are functions of the rate of investment and of vacancies (as shown by equations (19) and (21)), they relate to them in opposite ways: capital values are a positive function of the investment rate while labor values are a negative function of this rate; labor values are a positive function of the vacancy rate, while capital values are a negative function of this rate. This sign switch is due to the negative value of the interaction term parameters e_{31} and e_{32}. Moreover, the price of investment appears in the equation for capital values (equation (19)) but not in that for labor values.(equation (21)).

Third, as the relative price of capital $(\frac{p_t^I}{\frac{f_t}{k_t}})$ dominates the asset value of capital $\left(\frac{Q_t^K}{(1-\tau_t)\frac{f_t}{k_t}}\right)$ these two series have high correlation (0.95) and the same volatility. The negative correlation of this price with the two decision variables (around -0.50 for both) is consistent with its negative theoretical effect.

Fourth, labor asset values $(\frac{Q_t^N}{(1-\tau_t)\frac{f_t}{n_t}})$ have a positive correlation (0.64) with vacancy rates and with the investment rate, though weaker (0.36), as can be expected. Capital asset values have similar relations as the relative price of investment with the decision variables.

As noted, these correlations do not capture partial effects. Panel b of Table 3 quantifies the partial effects by presenting the moments of the elasticities of investment and vacancy rates with respect to their determinants.

Tax-adjusted labor asset values $(\frac{Q_t^N}{(1-\tau_t)\frac{f_t}{n_t}})$ have stronger effects than capital values $(\frac{Q_t^K}{(1-\tau_t)\frac{f_t}{k_t}})$ on both decision variables – mean elasticities of 0.78 and 0.90 as opposed to 0.22 and 0.10 with respect to the investment rate and the vacancy rate, respectively.

The effect of the job filling rate from non-employment (q_t^1) is positive on average with respect to investment and negative with respect to vacancies, as the present value effect dominates the costs effect for the former and is dominated for the latter. The rate from other employment (q_t^2) has a positive effect on both. Hence, as labor market conditions become tighter, investment rises but the effect on vacancy creation depends on the particular hiring flow in question.

The current corporate tax rate has a positive effect, ceteris paribus, which is much stronger than that of the asset value (of which it is a part). Investment-tax elasticity is much higher than vacancy-tax elasticity.

Summing up the key findings, labor asset values and capital asset values are weakly (and negatively) correlated. The former have stronger partial effects on the decision variables and are positively correlated with them; they are also more volatile. Capital asset values have weaker partial effects on the decision variables and are negatively correlated with them. The dominant component of these capital asset values is the relative price of investment. This structure engenders highly correlated decision variables.

6 Exploring the Role of Asset Values: Methodology

This section delineates the empirical methodology to be used and I begin by outlining its rationale. The idea is to use the estimated asset values to forecast vacancy rates and investment rates over the cycle and to forecast cyclical fluctuations in GDP itself. In sub-section 6.1, I explain why the asset values estimated above are natural candidates to be such predictors. In sub-section 6.2, I present the LP-IV methodology used to make these predictions, employing three technology-related shocks that are included in the model presented above. In sub-section 6.3 I present a methodology to make predictions of NBER-dated recessions using asset values and comparing their performance to prevalent predictors. Finally, sub-section 6.4 expounds on a cyclical analysis of contemporaneous co-movement. The results of implementing these methodologies are presented and discussed in the next section.

6.1 Background

Asset values encapsulate firms expectations about the future. Stock and Watson (2003) offered a review and analysis of the role of asset prices in forecasting output and inflation. They departed from the observation that

> "Because asset prices are forward-looking, they constitute a class of potentially useful predictors of inflation and output growth. The premise that interest rates and asset prices contain useful information about future economic developments embodies foundational concepts of macroeconomics." (p.788)

But their review of empirical analyses led to some negative conclusions, including the statement whereby:

> "the variables with the clearest theoretical justification for use as predictors often have scant empirical predictive content..." (p.801)

More recently these authors have emphasized FAVAR and SVAR methods in Macroeconomics (see Stock and Waston (2016)). They noted that the use of dynamic factor models in forecasting has had relatively more success than that implied by the quote above.

Taking another step, discussing the methodology used here, the LP-IV method, Stock and Watson (2018, p. 918) note that external instruments can be used to estimate dynamic causal effects directly without an intervening VAR step. The use of such external instruments facilitates credible identification, obtained using variation in the shock of interest that is distinct from the macroeconomic shocks hitting the economy. They express the view that this research programme holds out the potential for more credible identification than the one provided by SVARs identified using internal restrictions.

In the current context, labor and capital asset values are potential predictors and various technology-related shocks can act as the relevant instruments. The empirical questions here are – how useful and how good are these asset values as predictors. I now turn to describe the methodology and the shocks to be used as instruments.

6.2 Shocks Series and the LP-IV Methodology

Asset values are the expected present values of future marginal productivities, adjusted for separation or deprecation, wages, and taxes. The natural drivers of these productivities are technology-related shocks. The model of Section 3 incorporates three such shocks. I explore these shocks for the aggregate U.S. economy, taken from the authors of the following papers, for the period 1994-2016 used above.

The TFP shock series is taken from an online data base described in Fernald (2014). In terms of equation (2) above, this is utilization-adjusted ε_t^f. In the empirical work which follows I will denote it ε_t^{TFP}.

The unanticipated IST shock series ε_t^I are taken from Ben Zeev and Khan (2015). Ben Zeev (2018) shows in his equations (2) and (3) the relevant stochastic specification, akin to equation (7) above. I will denote it ε_t^{IST}.

The worker matching shocks series ε_t^μ was generated by Furlnaetto and Groshenny (2016 a,b). They derive the series within a medium-scale DSGE model. Their model features a Cobb Douglas matching function, with a matching technology shock process akin to equation (5) above. I will denote it $\varepsilon_t^{matching}$.

As noted, I use local projections-instrumental variables (LP-IV) methods to analyze the IRFs of the relevant variables in response to each shock. The analysis follows the initial contribution of Jordà (2005), extended to an IV context by several authors, including Jordà, Schularick, and Taylor (2015, 2019). These authors have shown how to use this method employing shocks as instruments. Stock and Watson (2018) delineate and discuss the conditions of relevance and exogeneity under which external instrument methods produce valid inference on structural impulse response functions. The use of the LP methodology to examine the impact of macroeconomic shocks is reviewed and discussed by Ramey (2016). The rationale for this methodology is that it is a direct forecasting method, as distinct from iterated forecasting, and puts fewer restrictions on the IRFs relative to VARs.

The following LP equation is run at second stage:

$$Y_{i,t+h} = c_{i,h} + \lambda_h^N \widehat{\frac{Q_t^N}{(1-\tau_t)\frac{f_t}{n_t}}} + \lambda_h^K \widehat{\frac{Q_t^K}{(1-\tau_t)\frac{f_t}{k_t}}} + \mathbf{\Gamma}'_{i,h}\mathbf{X}_t + e_{i,t+h} \tag{22}$$

On the LHS, $Y_{i,t+h}$ is a predicted variable indexed i at horizon h. On the RHS, the fitted asset values $\widehat{\frac{Q_t^N}{\frac{f_t}{n_t}}}, \widehat{\frac{Q_t^K}{\frac{f_t}{k_t}}}$, emerging from the first stage, act as shocks. Each regression has a constant ($c_{i,h}$) and an error term ($e_{i,t+h}$). $\mathbf{X}_t$ is a vector of control variables. The estimated coefficients are λ_h^i and the vector $\mathbf{\Gamma}_{i,h}$, respectively. A plot of the λ_h^i traces out the effect of the fitted asset values on the variable $Y_{i,t+h}$, i.e., the impulse response function (IRF) of the variable to the shock. I compute Newey-West HAC standard errors.

The fitted asset values $\widehat{\frac{Q_t^N}{\frac{f_t}{n_t}}}, \widehat{\frac{Q_t^K}{\frac{f_t}{k_t}}}$ emerge from the first stage where one estimates:

$$\frac{Q_t^i}{(1-\tau_t)\frac{f_t}{(i)_t}} = a + \mathbf{b}'\mathbf{Z}_t + \mathbf{c}'\mathbf{X}_t + v_t \tag{23}$$

and where:

$$\begin{aligned}
\frac{Q_t^i}{(1-\tau_t)\frac{f_t}{(i)_t}} &\in \{\frac{Q_t^N}{(1-\tau_t)\frac{f_t}{n_t}}, \frac{Q_t^K}{(1-\tau_t)\frac{f_t}{k_t}}\} \\
Y_{i,t+h} &\in \{\frac{v_{t+h}}{n_{t+h}}, \frac{i_{t+h}}{k_{t+h}}, f_{t+h}, \} \\
\mathbf{Z}_t &\in \{\varepsilon_t^{TFP}, \varepsilon_t^{IST}, \varepsilon_t^{matching}\}
\end{aligned}$$

In this equation a is a constant, $\mathbf{Z}_t$ is the vector of the three shocks, and there is an error term v_t; $\mathbf{b}$ and $\mathbf{c}$ are vectors of coefficients.

The rationale is that asset values ($\frac{Q_t^i}{(1-\tau_t)\frac{f_t}{(i)_t}}$), driven by shocks ($\mathbf{Z}_t$), predict firms decisions ($\frac{v_{t+h}}{n_{t+h}}, \frac{i_{t+h}}{k_{t+h}}$) and ultimately, though less directly, GDP (f_{t+h}).

Estimation of equations (22)-(23) requires the choice of control variables ($\mathbf{X}_t$), and I present three alternative specifications. I use linear-quadratic detrending throughout. I report R^2 statistics and various F tests to evaluate the results.

6.3 Predicting Recessions

To evaluate how well asset values predict recessions in the U.S. economy, I use a methodology proposed by Berge and Jordà (2011), which I briefly delineate here (fully explained on pages 249 to 254 of their paper).

First, define the following: $S_t \in \{0,1\}$ is the true state of the economy, with 0 denoting a state of expansion and 1 a state of recession; an index Θ_t; and a threshold c. Whenever $\Theta_t \geq c$ the prediction is for a recession and whenever $\Theta_t < c$ the prediction is for an expansion.

Now define the following conditional probabilities:

$$
\begin{aligned}
TP(c) &= P[\Theta_t \geq c \mid S_t = 1] \\
FP(c) &= P[\Theta_t \geq c \mid S_t = 0]
\end{aligned}
\tag{24}
$$

where TP (FP) stands for true positive (false positive).

To judge performance, one can plot receiver operating characteristic (ROC) curves. Such a curve is a graphical plot illustrating the diagnostic ability of a binary classifier system as its discrimination threshold is varied. This is done in TP rate and FP rate space.[12] The curves to be presented below are the ROC curves for chosen optimal c.[13] If Θ_t is unrelated to the underlying state of the economy S_t and is an entirely uninformative classifier, $TP(c) = FP(c)$ and the ROC curve is the 45° line, a benchmark with which to compare classifiers.

A useful statistic is the area under the curve ($AUROC$), which can be computed according to:

$$
\begin{aligned}
AUROC &= \int_{o}^{1} ROC(r)dr \\
AUROC &\in [0.5, 1]
\end{aligned}
\tag{25}
$$

where a perfect classifier gets a value of 1 and a coin-toss classifier gets a value of 0.5.

I compare the predictions generated by the rate of change of asset values derived here to those generated by a few prevalent indicators using ROC curves and the $AUROC$ statistic.

6.4 Cyclical Analysis

Subsequently, I use the results of LP-IV estimation for the following cyclical analysis. Consider first an OLS regression of the form:

$$
x_{jt} = a_j + b_j f_t + e_{jt} \tag{26}
$$

The estimated coefficient b_j is an indicator of the cyclicality of variable x_{jt} with respect to GDP f_t. This is an estimate unconditioned by shocks, and does not take into account any dynamics. Daly, Fernald, Jordà, and Nechio (2018) suggest using the aforegoing LP estimates, $\widehat{\lambda}_i^j$,to estimate a shock z-conditional b_j using Classical Minimum Distance (CMD) as follows:

[12]The ROC curve is represented with the Cartesian convention $\{ROC(r), r\}_{r=0}$ and where $ROC(r) = TP(c)$ and $r = FP(c)$.

[13]Doing so I use the Berge and Jordà (2011) procedure to determine an optimal threshold (see their pages 251-2). This is determined by the point the slope of the ROC curve equals the expected marginal rate of substitution between the net utility of accurate expansion and recession prediction.

$$\widehat{b}_{zj} = (\widehat{\boldsymbol{\lambda}}_z^{f'} M \widehat{\boldsymbol{\lambda}}_z^{f})^{-1} (\widehat{\boldsymbol{\lambda}}_z^{f'} M \widehat{\boldsymbol{\lambda}}_z^{j}) \tag{27}$$

with variance of $\widehat{b}_{zj}$ given by:

$$v_{zj} = (\widehat{\boldsymbol{\lambda}}_z^{f'} M \widehat{\boldsymbol{\lambda}}_z^{f})^{-1} \tag{28}$$

and where:

$$M = \left(\Omega_z^j\right)^{-1} \tag{29}$$

$\widehat{\boldsymbol{\lambda}}_z^f$ is the $h \times 1$ vector of LP coefficients of shock z on f, $\widehat{\boldsymbol{\lambda}}_z^j$ is the $h \times 1$ vector of LP coefficients of shock z on variable j, and Ω_z^j a diagonal matrix with variance estimates of $\widehat{\boldsymbol{\lambda}}_z^j$ from equation (22).

The intuition here is to find the $\widehat{b}_{zj}$ which makes the IRF of f (to a shock z) as close as possible to the IRF of variable j (to a shock z). Hence b_j and $\widehat{b}_{zj}$ can be denoted static and dynamic coefficients, respectively.

7 Asset Values: Predictive Role and Cyclical Behavior

I examine how U.S. macro evidence bears out the implications of the model. First, I focus on the estimated asset values as predictors of real activity. I do so using the methodology outlined in Sub-section 6.2. Second, I look at how good asset values are as predictors of recessions, using the methodology of Sub-section 6.3. I discuss the broader implications of this predictive performance. Finally, I look at the cyclical behavior of these values and relate them to the cyclical behavior of the decision variables, using the methodology outlined in Sub-section 6.4.

7.1 Asset Values Forecasts of Vacancies, Investment, and GDP

I try three different specifications of the control variables $\mathbf{X}_t$ presented in panel a of Table 4.

Table 4

The first specification uses lagged values of the shocks and the current and lagged relative price of investment as the control variables. The second specification adds to these variables lagged values of GDP and of the real interest rate. The third expands this last set to include the real activity factor computed by McCracken and Ng (2016) in their analysis of FRED data, to be denoted MN factor 1 (see details in Appendix B).

Figure 1 shows the IRFs of vacancy rates, investment rates, and GDP for the $\widehat{\frac{Q_t^N}{(1-\tau_t)\frac{f_t}{n_t}}}$, $\widehat{\frac{Q_t^K}{(1-\tau_t)\frac{f_t}{k_t}}}$ predictors.

Figure 1

The figure uses the different specifications of Table 4a, and plots 68% and 95% confidence bands.

The positive effects of the fitted labor asset values $\widehat{\frac{Q_t^N}{(1-\tau_t)\frac{f_t}{n_t}}}$ on all three variables are apparent. They are immediate for vacancy rates, while for investment rates there is some delay, with a resulting hump shape. They are also stronger for vacancy rates. For all three variables, the effects last just over 2 years. The positive effects of the fitted capital asset value $\widehat{\frac{Q_t^K}{(1-\tau_t)\frac{f_t}{k_t}}}$ on all variables are also apparent but last a shorter time, a year or less.

Table 4 reports key statistics, as follows.

(i) F-stats of the first stage regression (panel b), showing how much the shocks (contained in $\mathbf{Z}_t$) are related to the fitted asset values $(\widehat{\frac{Q_t^N}{(1-\tau_t)\frac{f_t}{n_t}}}, \widehat{\frac{Q_t^K}{(1-\tau_t)\frac{f_t}{k_t}}})$. The panel indicates that the matching shock is strongly related to the labor asset value and that the IST shock is strongly related to the capital asset value. The TFP shock has variable effects depending on the specification.

(ii) the R^2 of the second stage regression (panel c), essentially showing how good is the forecasting value of the activity variables (contained in $Y_{i,t+h}$) by all right hand side variables. This panel indicates very high predictive performance, only somewhat diminishing at 8 quarters. GDP is particularly well predicted.

(iii) the F test statistic of the null hypothesis $H_0 : \lambda_h^N = \lambda_h^K = 0$ (panel d) showing the significance of asset values in the projections equations. It indicates that asset values are highly significant.

It can be asked whether similar good predictions can be generated by using the observed decision variables themselves, i.e., vacancy rates and investment rates, as well as the relative price of investment, as the predictors rather than using asset values. Appendix E examines this issue and finds that the results are much less clear in terms of predictive ability, so the reply to this question is negative.

7.2 Asset Values As Recession Predictors

I use the methodology of Berge and Jordà (2011) described in Sub-section 6.3 to examine asset values as predictors of recession. The analysis pertains to the period 1976-2016 which includes five recession episodes.[14] Specifically, I show the rate of change in $\frac{Q_t^N}{(1-\tau_t)\frac{f_t}{n_t}}$ and in $\frac{Q_t^K}{(1-\tau_t)\frac{f_t}{k_t}}$ between $t-4$ and t as predictors of period t being an NBER recession. I compare the predictive ability of asset values to two prominent indices reported by Berge and Jordà (2011), the CFNAI and the ADS index. The former, the Chicago Fed National Activity Index (CFNAI), is a monthly index constructed as a weighted average of 85 monthly indicators of national activity, and builds upon the

[14] I use the point estimates of row (c) in Table 1a to construct the rate of change of asset values.

real activity index constructed by Stock and Watson (1999).[15] The latter index is the Aruoba, Diebold, and Scotti (ADS) Business Conditions Index, maintained by the Federal Reserve Bank of Philadelphia. The ADS index is designed to track real business conditions at very high frequencies. It is based on a smaller number of indicators than CFNAI. [16]Additionally, I report the performance of the widely-used Excess Bond Premium (EBP), proposed by Gilchrist and Zakrajšek (2012). This is derived from a corporate bond credit spread (GZ) with a high information content for economic activity that is built from the bottom up, using secondary market prices of senior unsecured bonds issued by a large representative sample of U.S. non-financial firms. The EBP is extracted from the GZ spread by removing expected default risk of individual firms.[17]

Figure 2 presents two graphs for each predictive variable for the same period 1976-2016. One graph shows the *ROC* defined above and reports the AUROC statistic. The second graph shows the time series of the variable in question, the NBER-dated recessions in shaded regions, and the optimal threshold (c) used.

Figure 2

The rate of change of labor asset values has an AUROC statistic of 0.94 just slightly below that of the CFNAI and ADS (both 0.98). It is a better predictor than the EBP with an AUROC statistic of 0.88. The time series graphs are consistent with this description. The rate of change of capital asset values has an AUROC statistic of 0.90 and so performs somewhat less well than labor asset values. It is, for example, not as strong a predictor in the 1990-1 and 2001 recessions, judging by the time series.

Overall, it can concluded that asset values, and in particular labor values, are very good predictors of U.S. recessions.

7.3 Asset Values as Predictors: The Broader Context

The finding that the estimated asset values have the predictive performance reported in the preceding two sub-sections, suggests that they can be used as predictors and as sufficient statistics. The idea is that they are time-t asset prices that capture what firms expect of future flows from investment and hiring, discounted (taking into account depreciation/separation and discount rates). They thus embody in a parsimonious way, the current information set of the firm and its expectations of the future. Formally:

$$\frac{Q_t^K}{(1-\tau_t)\frac{f_t}{k_t}} = \frac{1}{(1-\tau_t)\frac{f_t}{k_t}} E_t \left[\rho_{t+1} (1-\tau_{t+1}) \begin{bmatrix} f_{k_{t+1}} - g_{k_{t+1}} \\ +(1-\delta_{t+1})(g_{i_{t+1}} + p^I_{t+1}) \end{bmatrix} \right] \tag{30}$$

[15]See https://www.chicagofed.org/publications/cfnai/index

[16]See https://www.philadelphiafed.org/research-and-data/real-time-center/business-conditions-index/

[17]See https://www.federalreserve.gov/econresdata/notes/feds-notes/2016/recession-risk-and-the-excess-bond-premium-20160408.html

$$\frac{Q_t^N}{(1-\tau_t)\frac{f_t}{n_t}} = \frac{1}{(1-\tau_t)\frac{f_t}{n_t}} E_t \left[\rho_{t+1} (1-\tau_{t+1}) \left[\begin{array}{c} f_{n_{t+1}} - g_{n_{t+1}} - w_{t+1} \\ +(1-\psi_{t+1}) \frac{g_{v_{t+1}}}{q_{t+1}} \end{array} \right] \right] \tag{31}$$

Asset values capture the expected, discounted net productivity in the future of each input. Practically, any aggregate model that features forward-looking firm production may make use of such asset prices. This includes DSGE models, in particular the one proposed by Jaimovich and Rebelo (2009), which stresses forward-looking news mechanisms.[18]There is theoretical consistency of the current analysis with this broader framework.

Given that the data used here to construct asset values do not rely on financial markets data, they are not subject to distortions in these markets, such as asset price bubbles, noise trading, short run misvaluations, etc. As noted, the analysis does not make use of financial data and is not predicated on such data. It is, however, consistent with movements in financial asset prices, in particular stock prices. Such consistency was demonstrated by Merz and Yashiv (2007); the latter paper shows that this set-up can account well for the movements of aggregate U.S stock prices.

7.4 Asset Values Along the Cycle

Turning to cyclical analysis of contemporaneous co-movement, Table 5 reports the point estimates and standard errors of the static b_j from equation (26) and the dynamic b_{ij} from equation (27). A positive (negative) coefficient indicates pro-(counter-) cyclicality.

Table 5

Without conditioning on any shock, the decision variables are pro-cyclical and so is the labor asset value; the capital asset value, dominated by the relative price of investment, is counter-cyclical.

Conditioning on asset values $(\widehat{\frac{Q_t^N}{(1-\tau_t)\frac{f_t}{n_t}}}, \widehat{\frac{Q_t^K}{(1-\tau_t)\frac{f_t}{k_t}}})$ as predictors and using the three specifications of the control variables ($\mathbf{X}_t$), the results, for the most part, stay qualitatively the same. Quantitatively, going from the static coefficients in the first column to the dynamic coefficients in the next two columns, the following changes take place.

(i) the vacancy rate coefficient is higher, i.e., the pro-cyclicality is stronger

(ii) the investment rate coefficient is higher, i.e., the pro-cyclicality is stronger, when using $\widehat{\frac{Q_t^K}{(1-\tau_t)\frac{f_t}{k_t}}}$ as the predictor;

(iii) the labor asset value coefficient is higher when $\widehat{\frac{Q_t^N}{(1-\tau_t)\frac{f_t}{n_t}}}$ is the predictor and turns insignificant when $\widehat{\frac{Q_t^K}{(1-\tau_t)\frac{f_t}{k_t}}}$ is the predictor;

[18]Barsky and Sims (2011) report an empirical anlaysis of this framework; Walentin (2014) shows that stock price movements can also be correctly captured in this model.

(iv) the counter-cyclicality of capital asset values weakens and is sometimes insignificant.

This means that across variables (decision variables and asset values), the patterns of co-movement with GDP, conditioning on the three technology-related shocks via the predicted asset values, are the same as the co-movement with GDP seen in the data unconditionally. This may be suggestive of the significant role played by the three shocks in generating the data.

8 Conclusions

The key findings of this paper may be summarized as follows. Unobserved capital and labor asset values are estimated at reasonable values and have useful, predictive content. They are weakly and negatively correlated (between them). Labor values have stronger partial effects on the decision variables (investment and hiring) and are positively correlated with them. Capital asset values have weaker partial effects on the decision variables and are negatively correlated with them. The dominant component of the latter (capital asset) values is the relative price of investment. This structure engenders highly correlated decision variables. Asset values capture succinctly the available information and the current expectations of firms. They thus predict well future investment and hiring, as well as predicting cyclical fluctuations in GDP, including good predictive performance for recessions.

It is natural to seek to implement this framework in a micro setting. A major challenge here pertains to data availability. What is needed is a panel data set, which has to include all the variables discussed above. A key problem is that gross hiring flows (h_t^1, h_t^2 in the terminology used here), gross worker separations (ψ_t), vacancies (v_t), and investment prices (p_t^I) are often unavailable, or not fully available, at the micro level (be it industry, firm, or establishment level); moreover, real wage data, to match these other variables, are needed. All variables must be at the quarterly frequency, for a sufficiently long period of time, to allow for cyclical analysis.

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9 Tables and Figures

Table 1
GMM Estimation Results

a. Preferred Specifications

	specification	η_1	η_2	η_{31}	η_{32}	e_1	e_2	e_{31}	e_{32}	λ_1	λ_2	α	$J(\chi^2)$
a	all free	1.99	**1.98**	1.02	1.00	75	7	−12	−8	**0.64**	0.20	**0.67**	62
		(1.69)	(0.86)	(1.06)	(1.45)	(397)	(10)	(60)	(63)	(0.10)	(0.14)	(0.02)	(0.44)
b	η_s restricted	2	2	1	1	**81**	**8**	**−11**	**−10**	**0.65**	**0.21**	**0.66**	65
		–	–	–	–	(8)	(2)	(2)	(3)	(0.06)	(0.07)	(0.01)	(0.49)
c	η_s restricted	2	2	1	–	**80**	**2.4**	**−12**	–	0.34	–	**0.64**	81
	$e_{32} = 0; \lambda_2 = 0$	–	–	–	–	(15)	(1.2)	(4)		(0.24)		(0.01)	(0.11)
	1976-2016												

b. Standard Specifications

	specification	η_1	η_2	η_{31}	η_{32}	e_1	e_2	e_{31}	e_{32}	λ_1	λ_2	α	$J\ (\chi^2)$
a	Tobin's Q for K	2	–	–	–	**31.7**	0	0	0	–	–	**0.70**	47
		–				(12.9)	–	–	–			(0.00)	(0.14)
b	Tobin's Q for N	–	2	–	–	–	2.72	0	0	0.44	0.11	**0.67**	**58**
		–	–				(6.76)	–	–	(0.47)	(0.86)	(0.03)	(0.001)
c	Standard Matching Model	–	1	–	–	–	**0.34**	0	0	0	0	**0.65**	**49**
							(0.08)	–	–	–	–	(0.01)	(0.02)

Notes:

1. The tables report GMM point estimates with standard errors in parentheses. Significant estimates are bolded. The J-statistic is reported with p value in parentheses.

2. The sample period is 1994:1 – 2016:4 unless noted otherwise. In all rows, except (a) of Panel a, the η_s are restricted as indicated.

Table 2
Moments of the Estimated Frictions

a. Preferred Specifications

	specification		$\frac{g_t}{f_t}$	$\frac{\frac{\frac{g_{i,t}}{f_t}}{k_t}}{\frac{\frac{p_t^I}{f_t}}{k_t}} = \frac{\widetilde{Q}_t^K}{Q_t^P}$	$\frac{\frac{g_{v,t}}{q_t}}{w_t} = \frac{\frac{Q_t^N}{(1-\tau_t)}}{w_t}$
a	all free	mean	0.032	0.027	0.50
		std.	0.004	0.013	0.05
b	η_s restricted	mean	0.033	0.024	0.55
	1994-2016 sample	std.	0.004	0.014	0.06
c	η_s restricted; $e_{32} = \lambda_2 = 0$	mean	0.032	0.034	0.65
	1976-2016 sample	std	0.015	0.024	0.34

b. Standard Specifications

	specification		$\frac{g_t}{f_t}$	$\frac{\frac{\frac{g_{i,t}}{f_t}}{k_t}}{\frac{\frac{P_t^I}{f_t}}{k_t}} = \frac{\frac{\widetilde{Q}_t^K}{(1-\tau_t)}}{p_t^I}$	$\frac{\frac{g_{v,t}}{q_t}}{w_t} = \frac{\frac{Q_t^N}{(1-\tau_t)}}{w_t}$
a	Tobin's Q for K	mean	0.011	0.075	–
		std.	0.002	0.008	–
b	Tobin's Q for N	mean	0.025	–	0.47
		std.	0.005	–	0.08
c	Standard Matching Model	mean	0.068	–	0.64
		std	0.011	–	0.10

Notes:
1. The series were generated using the corresponding estimates from Table 1.
2. Panels a and b report means and standard deviations of time series of the variables listed in the top rows.

Table 3
Estimated Asset Values and the Decision Variables

a. Second Moments

Standard Deviation

	$\frac{Q_t^K}{(1-\tau_t)\frac{f_t}{k_t}}$	$\frac{Q_t^N}{(1-\tau_t)\frac{f_t}{n_t}}$	$\frac{p_t^I}{\frac{f_t}{k_t}}$	$\frac{v_t}{n_t}$	$\frac{i_t}{k_t}$	$\frac{f_t}{f_{t-1}}$
std.	0.045	0.081	0.045	0.17	0.08	0.01

Correlations

	$\frac{Q_t^K}{(1-\tau_t)\frac{f_t}{k_t}}$	$\frac{Q_t^N}{(1-\tau_t)\frac{f_t}{n_t}}$	$\frac{p_t^I}{\frac{f_t}{k_t}}$	$\frac{v_t}{n_t}$	$\frac{i_t}{k_t}$	$\frac{f_t}{f_{t-1}}$
$\frac{Q_t^K}{(1-\tau_t)\frac{f_t}{k_t}}$	1	-0.13	0.95	-0.34	-0.24	-0.42
$\frac{Q_t^N}{(1-\tau_t)\frac{f_t}{n_t}}$		1	-0.23	0.64	0.36	0.26
$\frac{p_t^I}{\frac{f_t}{k_t}}$			1	-0.53	-0.49	-0.42
$\frac{v_t}{n_t}$				1	0.88	0.22
$\frac{i_t}{k_t}$					1	0.09
$\frac{f_t}{f_{t-1}}$						1

Notes:

1. The asset values series were generated using the estimation results of row (b) in Table 1a.

2. All the series are in logs.

b. Elasticities of the Decision Variables ($\frac{i_t}{k_t}$, $\frac{v_t}{n_t}$) with Respect to Their Determinants

		$\frac{i_t}{k_t}$	$\frac{v_t}{n_t}$
Determinants		*mean (std)*	*mean (std)*
asset value effects	$\frac{\partial \cdot}{\partial \frac{Q_t^K}{(1-\tau_t)\frac{f_t}{k_t}}} \frac{\frac{Q_t^K}{(1-\tau_t)\frac{f_t}{k_t}}}{\cdot}$	0.22	0.10
		(0.11)	(0.05)
	$\frac{\partial \cdot}{\partial \frac{Q_t^N}{(1-\tau_t)\frac{f_t}{n_t}}} \frac{\frac{Q_t^N}{(1-\tau_t)\frac{f_t}{n_t}}}{\cdot}$	0.78	0.90
		(0.11)	(0.05)
investment price effects	$\frac{\partial \cdot}{\partial \frac{p_t^I}{(1-\tau_t)\frac{f_t}{k_t}}} \frac{\frac{p_t^I}{(1-\tau_t)\frac{f_t}{k_t}}}{\cdot}$	−9.58	−4.39
		(1.36)	(0.59)
job-filling rates effects	$\frac{\partial \cdot}{\partial q_t^1} \frac{q_t^1}{\cdot}$	0.10	−0.58
		(0.07)	(0.07)
	$\frac{\partial \cdot}{\partial q_t^2} \frac{q_t^2}{\cdot}$	0.60	0.39
		(0.13)	(0.07)
corporate tax effects	$\frac{\partial \cdot}{\partial \tau_t} \frac{\tau_t}{\cdot}$	2.24	1.31
		(0.23)	(0.11)

Notes:
1. Point $\cdot$ indicates $\frac{i_t}{k_t}$, $\frac{v_t}{n_t}$
2. The table uses estimation results of row (b) in Table 1a.
3. See Appendix D for definitions and derivations of the elasticities.

Table 4
The LP-IV Regressions

a. Control Variables $\mathbf{X}_t$

Specification	Control Variables $(j=1,2)$
1	$\mathbf{Z}_{t-j}, \frac{p_t^I}{\frac{f_t}{k_t}}, \frac{p_{t-j}^I}{\frac{f_{t-j}}{k_{t-j}}}$
2	$\mathbf{Z}_{t-j}, \frac{p_t^I}{\frac{f_t}{k_t}}, \frac{p_{t-j}^I}{\frac{f_{t-j}}{k_{t-j}}}, f_{t-j}, r_{t-j}$
3	$\mathbf{Z}_{t-j}, \frac{p_t^I}{\frac{f_t}{k_t}}, \frac{p_{t-j}^I}{\frac{f_{t-j}}{k_{t-j}}}, f_{t-j}, r_{t-j}, MNfactor1_{t-j}$

b. 1st stage F stats

specification	$\frac{Q_t^N}{(1-\tau_t)\frac{f_t}{n_t}}$			$\frac{Q_t^K}{(1-\tau_t)\frac{f_t}{k_t}}$		
	ε_t^{TFP}	ε_t^{IST}	$\varepsilon_t^{matching}$	ε_t^{TFP}	ε_t^{IST}	$\varepsilon_t^{matching}$
1	43.9	2.2	9.7	0.5	1.3	0.0
2	16.5	1.5	6.9	12.1	33.7	1.4
3	4.1	1.4	13.4	4.9	39.6	2.3

c. 2nd stage $\mathbf{R}^2$

specification		f			$\frac{v}{n}$			$\frac{i}{k}$		
	h	1	4	8	1	4	8	1	4	8
1		0.97	0.95	0.91	0.75	0.64	0.47	0.78	0.80	0.52
2		0.99	0.95	0.94	0.92	0.70	0.66	0.96	0.86	0.65
3		0.99	0.96	0.94	0.94	0.76	0.67	0.96	0.90	0.67

d. Restricted 2nd Stage Regression
F stats

$$H_0 : \lambda_h^K = \lambda_h^N = 0$$

specification		f			$\frac{v}{n}$			$\frac{i}{k}$		
	h	1	4	8	1	4	8	1	4	8
1		15.2^{***}	8.8^{***}	4.6^{**}	29.2^{***}	16.7^{***}	7.2^{***}	19.6^{***}	27.3^{***}	13.8^{***}
2		10.2^{***}	3.8^{**}	4.4^{**}	16.3^{***}	7.1^{***}	2.7^{*}	41.7^{***}	14.4^{***}	14.0^{***}
3		13.7^{***}	2.5^{*}	2.1	9.9^{***}	2.2	1.3	51.3^{***}	7.3^{***}	9.1^{***}

Notes:
1. The second stage regression is given by:

$$Y_{i,t+h} = c_{i,h} + \lambda_h^N \frac{\widehat{Q_t^N}}{(1-\tau_t)\frac{f_t}{n_t}} + \lambda_h^K \frac{\widehat{Q_t^K}}{(1-\tau_t)\frac{f_t}{k_t}} + \mathbf{\Gamma}_{i,h}'\mathbf{X}_t + e_{i,t+h}$$

First stage regression is given by:

$$\frac{Q_t^i}{(1-\tau_t)\,\frac{f_t}{(i)_t}} = a + \mathbf{b}'\mathbf{Z}_t + \mathbf{c}'\mathbf{X}_t + v_t$$

where

$$\begin{aligned} \frac{Q_t^i}{\frac{f_t}{(i)_t}} &\in \{\frac{Q_t^N}{\frac{f_t}{n_t}}, \frac{Q_t^K}{\frac{f_t}{k_t}}\} \\ Y_{i,t+h} &\in \{\frac{v_{t+h}}{n_{t+h}}, \frac{i_{t+h}}{k_{t+h}}, f_{t+h}, \} \\ \mathbf{Z}_t &\in \{\varepsilon_t^{TFP}, \varepsilon_t^{IST}, \varepsilon_t^{matching}\} \end{aligned}$$

2. The control variables specifications are given in panel a. All regressions include a linear quadratic time trend.

3. F statistics in panel b are t^2 values of the relevant $\mathbf{b}$ coefficients. In panel d they are given by $F(2, n-K) = \frac{\frac{R^2_{unrestricted} - R^2_{resticted}}{2}}{\frac{1-R^2_{unrestricted}}{n-K}}$.

4. The regressions use Newey-West HAC standard errors with the Bartlett kernel.

5. $^{***/**/*/NS}$ denote significance at 1%, 5%, 10% or not significant, respectively.

Table 5
Cyclicality of the Key Variables
Decisions Variables and Asset Values

a. Specification 1

	static	dynamic	
		$\widehat{\frac{Q_t^N}{(1-\tau_t)\frac{f_t}{n_t}}}$	$\widehat{\frac{Q_t^K}{(1-\tau_t)\frac{f_t}{k_t}}}$
$\frac{i}{k}$	1.48***	1.36***	2.23***
	(0.14)	(0.22)	(0.55)
$\frac{v_t}{n_t}$	2.98***	5.09***	2.99***
	(0.26)	(0.19)	(0.40)
$\frac{Q_t^N}{(1-\tau_t)\frac{f_t}{n_t}}$	0.76***	2.21***	-0.07^{NS}
	(0.20)	(0.41)	(0.35)
$\frac{Q_t^K}{(1-\tau_t)\frac{f_t}{k_t}}$	−0.61***	−0.42***	-0.11^{NS}
	(0.10)	(0.14)	(0.20)

b. Specification 2

	static	dynamic	
		$\widehat{\frac{Q_t^N}{(1-\tau_t)\frac{f_t}{n_t}}}$	$\widehat{\frac{Q_t^K}{(1-\tau_t)\frac{f_t}{k_t}}}$
$\frac{i}{k}$	1.48***	1.20***	2.48***
	(0.14)	(0.36)	(0.28)
$\frac{v_t}{n_t}$	2.98***	6.78***	4.01***
	(0.26)	(0.50)	(1.01)
$\frac{Q_t^N}{(1-\tau_t)\frac{f_t}{n_t}}$	0.76***	3.28***	-1.09^{NS}
	(0.20)	(0.48)	(0.67)
$\frac{Q_t^K}{(1-\tau_t)\frac{f_t}{k_t}}$	−0.61***	−0.49***	−0.58**
	(0.10)	(0.12)	(0.25)

c. Specification 3

	static	dynamic	
		$\widehat{\frac{Q_t^N}{(1-\tau_t)\frac{f_t}{n_t}}}$	$\widehat{\frac{Q_t^K}{(1-\tau_t)\frac{f_t}{k_t}}}$
$\frac{i}{k}$	1.48^{***}	1.28^{***}	2.49^{***}
	(0.14)	(0.31)	(0.29)
$\frac{v_t}{n_t}$	2.98^{***}	6.89^{***}	4.03^{***}
	(0.26)	(0.73)	(1.02)
$\frac{Q_t^N}{(1-\tau_t)\frac{f_t}{n_t}}$	0.76^{***}	3.14^{***}	-0.61^{NS}
	(0.20)	(0.69)	(0.51)
$\frac{Q_t^K}{(1-\tau_t)\frac{f_t}{k_t}}$	-0.61^{***}	-0.09^{NS}	-0.66^{***}
	(0.10)	(0.17)	(0.26)

Notes:

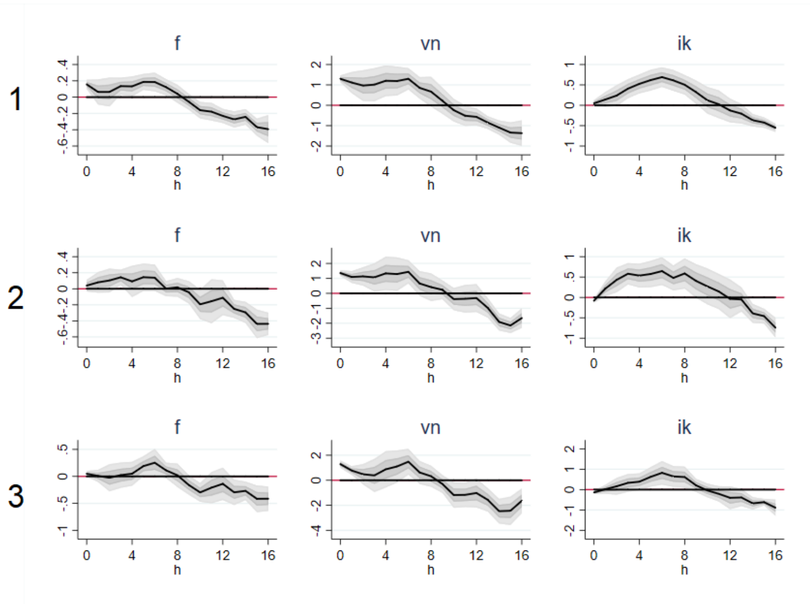
1. $***/**/*/NS$ denote significance at 1%, 5%, 10% or not significant, respectively.

2. Static columns report point estimates and standard errors in parentheses for b_j in equation (26): $x_{jt} = a_j + b_j f_t + e_{jt}$.

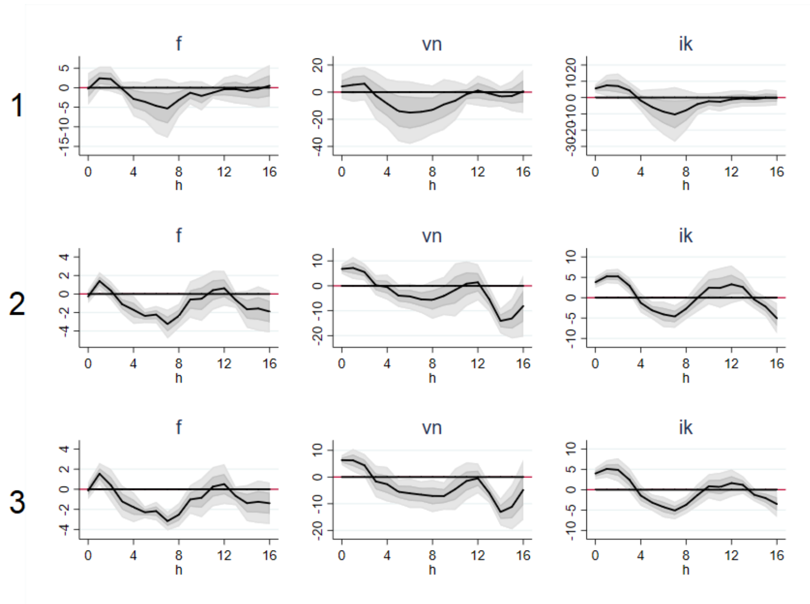
3. Dynamic columns report point estimates and standard errors in parentheses for b_{ij} in equation (27):$\widehat{b}_{ij} = (\widehat{\boldsymbol{\lambda}}_i^{f'} M \widehat{\boldsymbol{\lambda}}_i^{f})^{-1}(\widehat{\boldsymbol{\lambda}}_i^{f'} M \widehat{\boldsymbol{\lambda}}_i^{j})$.

4. All variables are logged.

Figure 1
LP-IV Projections of f_{t+h}, $\frac{v_{t+h}}{n_{t+h}}$, $\frac{i_{t+h}}{k_{t+h}}$ Using Asset Values as Predictors

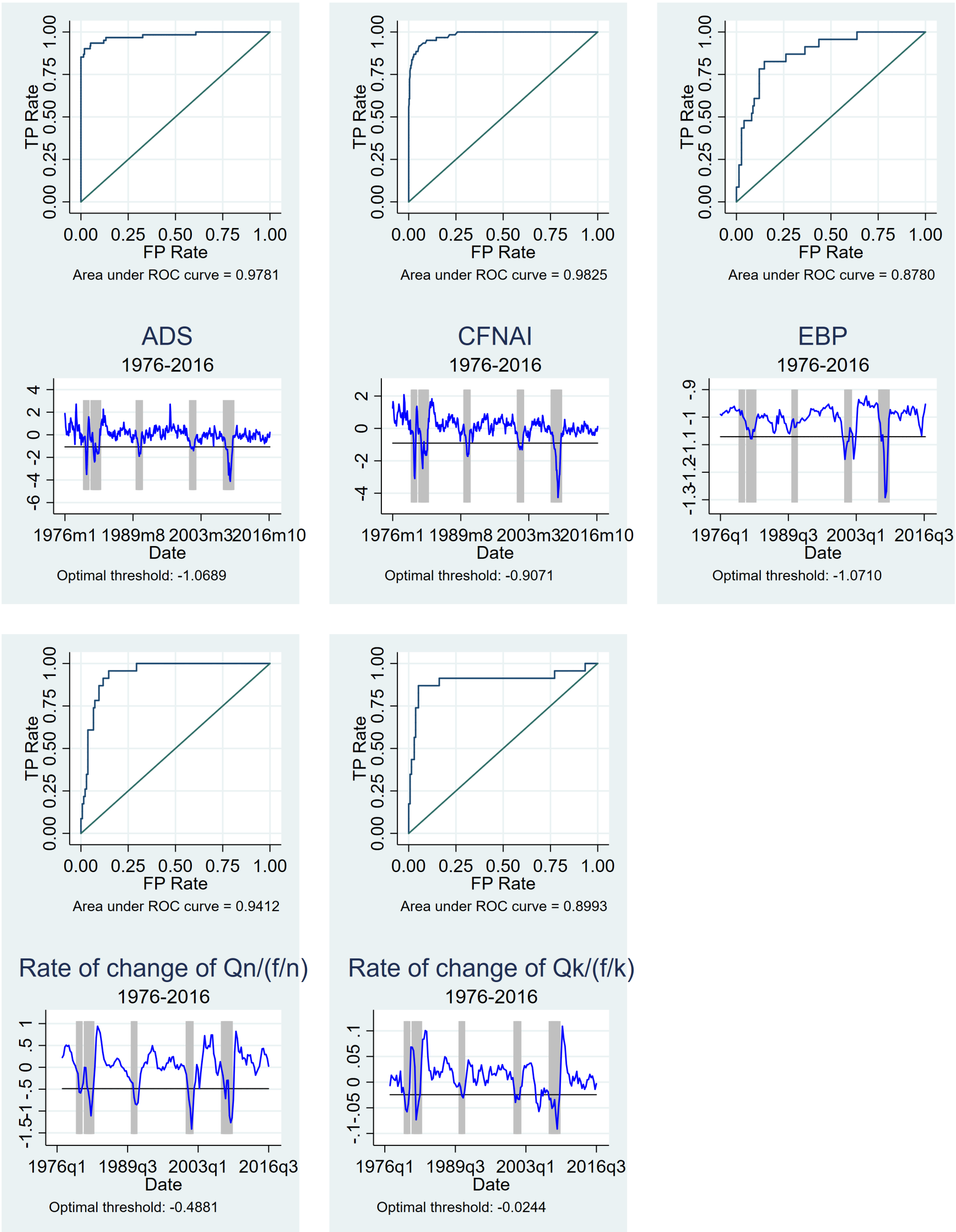


a. Impulse Response Functions of f_{t+h}, $\frac{v_{t+h}}{n_{t+h}}$, and $\frac{i_{t+h}}{k_{t+h}}$ using $\frac{\widehat{Q_t^N}}{\frac{f_t}{n_t}}$



b. Impulse Response Functions of f_{t+h}, $\frac{v_{t+h}}{n_{t+h}}$, and $\frac{i_{t+h}}{k_{t+h}}$ using $\frac{\widehat{Q_t^K}}{\frac{f_t}{k_t}}$

Figure 2
Predictive Ability



10 Appendix A: Derivation of Asset Values

I derive a general Q_t which is a function of Q_t^K and Q_t^N. The following derivations are based on Hayashi (1982).

10.1 Firm Profits, Cash Flows, and Values

Define firm profits π_t :

$$\pi_t = [f(k_t, n_t) - g(i_t, k_t, v_t, n_t)] - w_t n_t . \tag{32}$$

Define cash flow payments to firm owners as cf_t equal to profits after tax minus purchases of investment goods plus investment tax credits and depreciation allowances for new investment goods:

$$\begin{aligned} cf_t &= (1-\tau_t)\pi_t - (1-\chi_t - \tau_t D_t)\, \widetilde{p}_t^I\, i_t \\ &= (1-\tau_t)\left(f(k_t, n_t) - g(i_t, k_t, v_t, n_t) - w_t n_t - p_t^I i_t\right) \end{aligned} \tag{33}$$

The representative firm's value in period t, Q_t, is defined as follows:

$$Q_t = E_t\left[\rho_{t+1}\left(Q_{t+1} + cf_{t+1}\right)\right] . \tag{34}$$

This can be split into capital ϑ_t^k and labor values ϑ_t^n as follows:

$$Q_t = \vartheta_t^k + \vartheta_t^n = E_t\left[\rho_{t+1}\left(\vartheta_{t+1}^k + cf_{t+1}^k\right)\right] + E_t\left[\rho_{t+1}\left(\vartheta_{t+1}^n + cf_{t+1}^n\right)\right] , \tag{35}$$

Using the constant returns-to-scale properties of the production function f and of the cost function, g, and equation (33), decompose the stream of maximized cash flow payments as follows:

$$\begin{aligned} cf_t &= (1-\tau_t)\left(f_{k_t}k_t + f_{n_t}n_t - w_t n_t - p_t^I i_t - g_{k_t}k_t - g_{i_t}i_t - g_{v_t}v_t - g_{n_t}n_t\right) \\ &= (1-\tau_t)\left[\left(f_{k_t}k_t - p_t^I i_t - g_{k_t}k_t - g_{i_t}i_t\right) + \left(f_{n_t}n_t - w_t n_t - g_{v_t}v_t - g_{n_t}n_t\right)\right] \\ &\equiv cf_t^k + cf_t^n. \end{aligned} \tag{36}$$

10.2 Optimality Equations and Asset Values

Multiply throughout the FOC with respect to investment by i_t, the FOC with respect to capital by k_{t+1}, the FOC with respect to vacancies by v_t, and the one with respect to employment by n_{t+1} to get

$$(1-\tau_t)\left(p_t^I + g_{i_t}\right) i_t = i_t Q_t^K \tag{37}$$

$$(1-\tau_t)\, g_{v_t} v_t = v_t q_t Q_t^N \tag{38}$$

$$k_{t+1} Q_t^K = k_{t+1} E_t\left\{\rho_{t+1}\left[(1-\tau_{t+1})\left(f_{k_{t+1}} - g_{k_{t+1}}\right) + (1-\delta_{t+1}) Q_{t+1}^K\right]\right\} \tag{39}$$

$$n_{t+1} Q_t^N = n_{t+1} E_t\left\{\rho_{t+1}\left[(1-\tau_{t+1})\left(f_{n_{t+1}} - g_{n_{t+1}} - w_{t+1}\right) + (1-\psi_{t+1}) Q_{t+1}^N\right]\right\} \tag{40}$$

10.2.1 Capital

Insert the law of motion for capital into equation (37), roll forward all expressions one period, multiply both sides by ρ_{t+1} and take conditional expectations on both sides:

$$E_t\left[\rho_{t+1}\left(1-\tau_{t+1}\right)\left(p^I_{t+1}+g_{i_{t+1}}\right)i_{t+1}\right]=E_t\left\{\rho_{t+1}\left[k_{t+2}-(1-\delta_{t+1})k_{t+1}\right]Q^K_{t+1}\right\}. \quad (41)$$

Rearranging:

$$E_t\left[\rho_{t+1}(1-\delta_{t+1})\left(k_{t+1}Q^K_{t+1}\right)\right]=E_t\left\{\rho_{t+1}\left[\left(k_{t+2}Q^K_{t+1}-(1-\tau_{t+1})\left(p^I_{t+1}+g_{i_{t+1}}\right)i_{t+1}\right)\right]\right\} \quad (42)$$

Combining equations (36), (37), (39), and (42) yields:

$$k_{t+1}Q^K_t=E_t\left(\rho_{t+1}\left(cf^k_{t+1}+k_{t+2}Q^K_{t+1}\right)\right) \quad (43)$$

Rearranging:

$$E_t\left(\rho_{t+1}cf^k_{t+1}\right)=k_{t+1}Q^K_t-E_t\left(\rho_{t+1}k_{t+2}Q^K_{t+1}\right). \quad (44)$$

It follows from the definition of the firm's market value in equation (35) that

$$\vartheta^k_t-E_t\left(\rho_{t+1}\vartheta^k_{t+1}\right)=E_t\left(\rho_{t+1}cf^k_{t+1}\right). \quad (45)$$

Thus,

$$\vartheta^k_t-E_t\left(\rho_{t+1}\vartheta^k_{t+1}\right)=k_{t+1}Q^K_t-E_t\left(\rho_{t+1}k_{t+2}Q^K_{t+1}\right), \quad (46)$$

which implies

$$\vartheta^k_t=k_{t+1}Q^K_t. \quad (47)$$

10.2.2 Labor

Derive a similar expression for the case of labor. Inserting the law of motion for labor into equation (38), multiplying both sides by ρ_{t+1}, rolling forward all expressions by one period, taking conditional expectations, and combining with equations (36) and (40) get

$$E_t\left(\rho_{t+1}cf^n_{t+1}\right)=n_{t+1}Q^N_t-E_t\left(\rho_{t+1}n_{t+2}Q^N_{t+1}\right). \quad (48)$$

The definition of the firm's value in equation (35) implies that

$$\vartheta^n_t-E_t\left(\rho_{t+1}\vartheta^n_{t+1}\right)=E_t\left(\rho_{t+1}cf^n_{t+1}\right). \quad (49)$$

Thus,

$$\vartheta^n_t-E_t\left(\rho_{t+1}\vartheta^n_{t+1}\right)=n_{t+1}Q^N_t-E_t\left(\rho_{t+1}n_{t+2}Q^N_{t+1}\right). \quad (50)$$

This implies the following expression for the asset value of employment:

$$\vartheta^n_t=n_{t+1}Q^N_t. \quad (51)$$

10.2.3 Aggregation

Hence, the total value of a firm, Q_t, equals:

$$Q_t = \vartheta_t^k + \vartheta_t^n = k_{t+1}Q_t^K + n_{t+1}Q_t^N. \tag{52}$$

where the components are defined in equations (39) and (40), respectively.

11 Appendix B: The Data

11.1 Sample Statistics

Table B1 presents key sample statistics.

Table B1

Descriptive Sample Statistics
Quarterly, U.S. data

a. 1976:1-2016:4 ($n = 168$)

Variable	$\frac{f}{k}$	τ	$\frac{i}{k}$	δ	$\frac{wn}{f}$	$\frac{h^1}{n}$	ψ^1	ρ
Mean	0.14	0.37	0.024	0.02	0.62	0.126	0.125	0.99
Standard Deviation	0.01	0.05	0.003	0.003	0.03	0.010	0.011	0.005

b. 1994:1-2016:4 ($n = 92$)

Variable	$\frac{f}{k}$	τ	$\frac{i}{k}$	δ	$\frac{wn}{f}$	$\frac{h}{n} = \frac{h^1+h^2}{n}$	$\psi = \psi^1 + \psi^2$	ρ
Mean	0.15	0.34	0.026	0.02	0.61	0.177	0.176	0.99
Standard Deviation	0.01	0.005	0.002	0.002	0.03	0.012	0.012	0.004

11.2 Sources and Definitions

variable		**definition and source**
GDP	f	gross value added of NFCB; NIPA accounts, table 1.14, line 41
GDP deflator	p^f	price per unit of gross value added of NFCB; NIPA table 1.15, line 1
wage share	$\frac{wn}{f}$	numerator: compensation of employees in NFCB; see note 7
discount factor	ρ	based on non-durable consumption growth; NIPA Table 2.3.3, see note 1
employment	n	employment in nonfinancial corporate business sector; CPS, see note 2
hiring	h	gross hires; CPS, see note 2
separation rate	ψ	gross separations divided by employment; CPS; see note 3
vacancies	v	adjusted Help Wanted Index; Conference Board; see note 4
investment	i	gross investment in NFCB sector; BEA and Fed Flow of Funds; see note 5
capital stock	k	stock of private nonresidential fixed assets in NFCB sector; BEA and Fed Flow of Funds; see note 5
depreciation	δ	depreciation of the capital stock; BEA and Fed Flow of Funds; see note 5
price of capital goods	p^I	real price of new capital goods; NIPA and U.S. tax foundation; see note 6

The longest sample period is 1976:1-2016:4; all data are quarterly.

Notes:

1. *The discount rate and the discount factor*

The discount rate is based on a DSGE-type model with logarithmic utility $U(c_t) = \ln c_t$. Define the discount factor as $\rho_t \equiv \frac{1}{1+r_t}$

In this model:

$$U'(c_t) = U'(c_{t+1}) \cdot (1 + r_t) \tag{53}$$

Hence:

$$\rho_t = \frac{c_t}{c_{t+1}} \tag{54}$$

where c is non-durable consumption (goods and services) and 5% of durable consumption.

2. *Employment*

As a measure of employment in the nonfinancial corporate business sector (n) I take wage and salary workers in non-agricultural industries (series ID LNS12032187) less government workers (series ID LNS12032188), less self-employed workers (series ID LNS12032192). All series originate from CPS databases. I do not subtract workers in private households (the unadjusted series ID LNU02032190) from the above due to lack of sufficient data on this variable.

3. *Hiring and Separation Rates*

The aggregate flow from non-employment – unemployment (U) and out of the labor force (O) – to employment is to be denoted $OE + UE$ and the separation rate ψ_t is rate of the flow in the opposite direction, $EU + EO$. Worker flows within employment – i.e., job to job flows – are to be denoted EE.

I denote $\frac{h^1}{n} = \frac{OE+UE}{E}$ and $\frac{h^2}{n} = \frac{EE}{E}$ the rates of flows from non-employment and from other employment, respectively. The total flows rate is $\frac{h}{n} = \frac{h^1}{n} + \frac{h^2}{n}$.

Separation rates are given by $\psi = \psi^1 + \psi^2$, $\psi^1 = \frac{EO+EU}{E}$ and $\psi^2 = \frac{EE}{E} = \frac{h^2}{n}$.

Employment dynamics now satisfies:

$$\begin{aligned} n_{t+1} &= (1 - \psi_t^1 - \psi_t^2)n_t + h_t^1 + h_t^2 \\ &= (1 - \psi_t)n_t + h_t, \quad 0 \le \psi_t \le 1 \\ h_t^2 &= \psi_t^2 \end{aligned} \tag{55}$$

To calculate hiring and separation rates for the whole economy I use the following:

a. *The h_t^1 and ψ_t^1 flows.* I compute the flows between E (employment), U (unemployment) and O (not-in-the-labor-force) that correspond to the E,U,O stocks published by the CPS. The methodology of adjusting flows to stocks is taken from BLS, and is presented in Frazis et al (2005).[19]The data till 1990:Q1 were kindly provided by Ofer Cornfeld. The data from 1990:Q2 onwards were taken from the CPS.[20] Employment is the quarterly average of the original seasonally adjusted total employment series from BLS (LNS12000000).

b. *The h_t^2 and ψ_t^2 flows.* The data on EE, available only from 1994:Q1 onward, were computed by multiplying the percentage of people moving from one employer to another using Fallick and Fleischman (2004)'s[21]data by the NSA population series LNU00000000, taken from the CPS, completing several missing observations and performing seasonal adjustment.

4. *Vacancies*

I use the vacancies series based on the Conference Board Composite Help-Wanted Index that takes into account both printed and web job advertisements, as computed by Barnichon (2012).[22] The updated series is available at

https://sites.google.com/site/regisbarnichon/research/publications.

This index was multiplied by a constant to adjust its mean to the mean of the JOLTS vacancies series over the overlapping sample period (2001:Q1–2013:Q4). As this series is based on indices, in estimation I estimate a scaling parameter.

5. *Investment, capital and depreciation*

Quarterly series for real investment flow i_t, real capital stock k_t , and depreciation rates δ_t were constructed using the following series:

- The quantity index for net stock of fixed assets in NFCB (FAA table 4.2, line 37, BEA) as well as the 2009 current-cost net stock of fixed assets (FAA table 4.1, line 37, BEA).

- The chain-type quantity index for depreciation from FAA table 4.5, line 37. The current-cost depreciation estimates (and specifically the 2009 estimate) are given in FAA table 4.4, line 37.

- Historic-cost quarterly investment in private non-residential fixed assets by NFCB sector, the Flow of Funds accounts, atabs files, series FA105013005).

The methodology is explained in Yashiv (2016).[23]

6. *Real price of new capital goods*

[19]Frazis, Harley J., Edwin L. Robison, Thomas D. Evans and Martha A. Duff, 2005. Estimating Gross Flows Consistent with Stocks in the CPS, **Monthly Labor Review,** September, 3-9.

[20]See http://www.bls.gov/cps/cps_flows.htm

[21]Fallick and Fleischman, 2004. "Employer-to-Employer Flows in the U.S. Labor Market: The Complete Picture of Gross Worker Flows," FEDS #2004-34.

[22]Barnichon, Regis, 2012. "Vacancy Posting, Job Separation and Unemployment Fluctuations," **Journal of Economic Dynamics and Control** 36, 315-330.

[23]See Yashiv, Eran, 2016. "Capital Values and Job Values," **Review of Economic Dynamics** 19, 190-209.

In order to compute the real price of new capital goods, p^I, I use the price indices for output and for investment goods.

Investment in NFCB Inv consists of equipment Eq and structures St as well as intellectual property, which I do not include. I define the time-t price-indices for good $j = Eq, St$ as $\widetilde{p}_t^j$. The data are taken from NIPA table 1.1.4, lines 10, 11.

I take from http://www.federalreserve.gov/econresdata/frbus/us-models-package.htm the following tax -related rates:

a. The parameter τ – the statutory corporate income tax rate as reported by the U.S. Tax Foundation.

b. The investment tax credit on equipment and public utility structures, to be denoted ITC.

c. The percentage of the cost of equipment that cannot be depreciated if the firm takes the investment tax credit, denoted χ.

d. The present discounted value of capital depreciation allowances, denoted $ZPDE^{St}$ and $ZPDE^{Eq}$.

I then apply the following equations:

$$\begin{aligned} p^{Eq} &= \widetilde{p}^{Eq}\left(1-\tau_{Eq}\right) \\ p^{St} &= \widetilde{p}^{St}\left(1-\tau_{St}\right), \end{aligned}$$

$$\begin{aligned} 1-\tau^{S_t} &= \frac{\left(1-\tau\, ZPDE^{St}\right)}{1-\tau} \\ 1-\tau^{Eq} &= \frac{1-ITC-\tau ZPDE^{Eq}\left(1-\chi ITC\right)}{1-\tau} \end{aligned}$$

Subsequently I compute their change between $t-1$ and t (denoted by Δp_t^j) :

$$\frac{\Delta p_t^{Inv}}{p_{t-1}^{Inv}} = \omega_t \frac{\Delta p_t^{Eq}}{p_{t-1}^{Eq}} + \left(1-\omega_t\right)\frac{\Delta p_t^{St}}{p_{t-1}^{St}}$$

where

$$\omega_t = \frac{\begin{array}{c}(\text{nominal expenditure share of } Eq \text{ in } Inv)_{t-1} \\ +\ (\text{nominal expenditure share of } Eq \text{ in } Inv)_t\end{array}}{2}.$$

The weights ω_t are calculated from the NIPA table 1.1.5, lines 9,11.

I divide the series by the price index for output, p_t^f, to obtain the real price of new capital goods, p^I.

As all of these prices are indices, in estimation I estimate a scaling parameter e^a.

7. *Labor share*

NIPA table 1.14, line 20 (compensation of employees in NFCB) divided by line 17 in the same table (gross value added in NFCB).

11.3 Additional Variable Used in the LP-IV Analysis

The interpretation of the factor taken from McCracken and Ng (2016) in their analysis of FRED data factor is discussed on their pages 577-8, and is "activity, employment". I denote it MN Factor 1.

12 Appendix C: GMM Estimation of the FOC

This Appendix elaborates on the GMM estimation discussed in Section 4.

12.1 The Cost Function and its Derivatives

$$
g(\cdot) = \left[\begin{array}{c} \frac{e_1}{\eta_1}(\frac{i_t}{k_t})^{\eta_1} \\ +\frac{e_2}{\eta_2}\left[\frac{(1-\lambda_1-\lambda_2)v_t+\lambda_1 q_t^1 v_t+\lambda_2 q_t^2 v_t}{n_t}\right]^{\eta_2} \\ +\frac{e_{31}}{\eta_{31}}\left(\frac{i_t}{k_t}\frac{q_t^1 v_t}{n_t}\right)^{\eta_{31}} + \frac{e_{32}}{\eta_{32}}\left(\frac{i_t}{k_t}\frac{q_t^2 v_t}{n_t}\right)^{\eta_{32}} \end{array} \right] f(z_t, n_t, k_t). \tag{56}
$$

$$
\frac{g_{i_t}}{\frac{f_t}{k_t}} = \left[\begin{array}{c} e_1(\frac{i_t}{k_t})^{\eta_1 - 1} \\ +e_{31}\left(\frac{q_t^1 v_t}{n_t}\right)^{\eta_{31}}(\frac{i_t}{k_t})^{\eta_{31}-1} + e_{32}\left(\frac{q_t^2 v_t}{n_t}\right)^{\eta_{32}}(\frac{i_t}{k_t})^{\eta_{32}-1} \end{array} \right] \tag{57}
$$

$$
\frac{g_{v_t}}{\frac{f_t}{n_t}} = \left[\begin{array}{c} e_2\left[\frac{(1-\lambda_1-\lambda_2)v_t+\lambda_1 q_t^1 v_t+\lambda_2 q_t^2 v_t}{n_t}\right]^{\eta_2-1}\left[(1-\lambda_1-\lambda_2)+\lambda_1 q_t^1+\lambda_2 q_t^2\right] \\ +e_{31} q_t^1\left(\frac{i_t}{k_t}\right)^{\eta_{31}}\left(\frac{q_t^1 v_t}{n_t}\right)^{\eta_{31}-1} \\ +e_{32} q_t^2\left(\frac{i_t}{k_t}\right)^{\eta_{32}}\left(\frac{q_t^2 v_t}{n_t}\right)^{\eta_{32}-1} \end{array} \right] \tag{58}
$$

$$
\begin{aligned}
\frac{g_{k_t}}{\frac{f_t}{k_t}} &= -\left[e_1(\frac{i_t}{k_t})^{\eta_1} + e_{31}\left(\frac{q_t^1 v_t}{n_t}\frac{i_t}{k_t}\right)^{\eta_{31}} + e_{32}\left(\frac{q_t^2 v_t}{n_t}\frac{i_t}{k_t}\right)^{\eta_{32}}\right] \\
&\quad +(1-\alpha)\left[\begin{array}{c} \frac{e_1}{\eta_1}(\frac{i_t}{k_t})^{\eta_1} \\ +\frac{e_2}{\eta_2}\left[\frac{(1-\lambda_1-\lambda_2)v_t+\lambda_1 q_t^1 v_t+\lambda_2 q_t^2 v_t}{n_t}\right]^{\eta_2} \\ +\frac{e_{31}}{\eta_{31}}\left(\frac{i_t}{k_t}\frac{q_t^1 v_t}{n_t}\right)^{\eta_{31}} + \frac{e_{32}}{\eta_{32}}\left(\frac{i_t}{k_t}\frac{q2 v_t}{n_t}\right)^{\eta_{32}} \end{array} \right]
\end{aligned} \tag{59}
$$

$$
\begin{aligned}
\frac{g_{n_t}}{\frac{f_t}{n_t}} &= -\left[\begin{array}{c} e_2\left[\frac{(1-\lambda_1-\lambda_2)v_t+\lambda_1 q_t^1 v_t+\lambda_2 q_t^2 v_t}{n_t}\right]^{\eta_2} \\ +e_{31}\left(\frac{q_t^1 v_t}{n_t}\frac{i_t}{k_t}\right)^{\eta_{31}} + e_{32}\left(\frac{q_t^2 v_t}{n_t}\frac{i_t}{k_t}\right)^{\eta_{32}} \end{array} \right] \\
&\quad +\alpha\left[\begin{array}{c} \frac{e_1}{\eta_1}(\frac{i_t}{k_t})^{\eta_1} \\ +\frac{e_2}{\eta_2}\left[\frac{(1-\lambda_1-\lambda_2)v_t+\lambda_1 q_t^1 v_t+\lambda_2 q_t^2 v_t}{n_t}\right]^{\eta_2} \\ +\frac{e_{31}}{\eta_{31}}\left(\frac{i_t}{k_t}\frac{q_t^1 v_t}{n_t}\right)^{\eta_{31}} + \frac{e_{32}}{\eta_{32}}\left(\frac{i_t}{k_t}\frac{q_t^2 v_t}{n_t}\right)^{\eta_{32}} \end{array} \right]
\end{aligned} \tag{60}
$$

12.2 The Estimating Equations

12.2.1 The General Specifications

Replacing expected variables by actual ones and a rational expectations forecast error, the estimating equations are:

$$(1-\tau_t)\left(g_{i_t}+p_t^I\right)=\rho_{t+1}\left(1-\tau_{t+1}\right)\left[\begin{array}{c} f_{k_{t+1}}-g_{k_{t+1}} \\ +(1-\delta_{t+1})(g_{i_{t+1}}+p_{t+1}^I) \end{array}\right]+j_t^k \tag{61}$$

I estimate this equation after dividing throughout by $\frac{f_t}{k_t}$.

$$(1-\tau_t)\frac{g_{v_t}}{q_t}=\rho_{t+1}\left(1-\tau_{t+1}\right)\left[\begin{array}{c} f_{n_{t+1}}-g_{n_{t+1}}-w_{t+1} \\ +(1-\psi_{t+1})\frac{g_{v_{t+1}}}{q_{t+1}} \end{array}\right]+j_t^n \tag{62}$$

I estimate this equation after dividing throughout by $\frac{f_t}{n_t}$.

As explained in the text, estimation pertains to $\alpha, e_1, e_2, e_{31}, e_{32}, \eta_1, \eta_2, \eta_{31}, \eta_{32}, \lambda_1, \lambda_2$.

12.2.2 Tobin's Q Approach

This approach ignores the other factor of production (i.e., assumes no adjustment costs for it). For the investment in capital equation $e_2 = e_{31} = e_{32} = 0$ and $\eta_1 = 2$ and only equation (61) is estimated. For the vacancy creation equation $e_1 = e_{31} = e_{32} = 0$ and $\eta_2 = 2$ and only equation (62) is estimated.

12.2.3 The Standard Search and Matching Model

In this case $e_1 = e_{31} = e_{32} = 0, \eta_2 = 1, \lambda_1 = \lambda_2 = 0$ and there is only the hiring equation given by:

$$(1-\tau_t)\frac{e_2}{q_t}=\left[\rho_{t+1}\left(1-\tau_{t+1}\right)\frac{\frac{f_{t+1}}{n_{t+1}}}{\frac{f_t}{n_t}}\left[\alpha-\frac{w_{t+1}}{\frac{f_{t+1}}{n_{t+1}}}+(1-\psi_{t+1})\frac{e_2}{q_{t+1}}\right]\right]+j_t \tag{63}$$

This is estimated for e_2 and α.

12.3 Moment Conditions and Instruments

The moment conditions estimated are those obtained under rational expectations i.e., $E(\mathbf{Z}_t \otimes j_t) = 0$ where $\mathbf{Z}_t$ is the vector of instruments.

The instrument set consists of 8 lags of the following variables – the hiring rate ($\frac{h}{n}$) and the investment rate ($\frac{i}{k}$) for both equations; the rate of growth of output per unit of capital ($\frac{f}{k}$) and the depreciation rate (δ) for the investment equation; and the labor share ($\frac{wn}{f}$) and rate of separation (ψ) for the vacancies equation.

I report the J-statistic χ^2 test of the over-identifying restrictions. It should be noted that no restriction is placed on any parameter estimate.

13 Appendix D: Relations Between Asset Values and Decision Variables

13.1 Solutions

The model posits:

$$\frac{Q_t^K}{\frac{f_t}{k_t}} = (1-\tau_t)\left(\frac{g_{i_t}}{\frac{f_t}{k_t}} + \frac{p_t^I}{\frac{f_t}{k_t}}\right) \tag{64}$$

$$\frac{Q_t^N}{\frac{f_t}{n_t}} = (1-\tau_t)\,\frac{\frac{g_{v_t}}{q_t}}{\frac{f_t}{n_t}} \tag{65}$$

$$\frac{g_{i_t}}{\frac{f_t}{k_t}} = \left[\begin{array}{c} e_1(\frac{i_t}{k_t})^{\eta_1-1} \\ +e_{31}\left(\frac{q_t^1 v_t}{n_t}\right)^{\eta_{31}}(\frac{i_t}{k_t})^{\eta_{31}-1} + e_{32}\left(\frac{q_t^2 v_t}{n_t}\right)^{\eta_{32}}(\frac{i_t}{k_t})^{\eta_{32}-1} \end{array}\right] \tag{66}$$

$$\frac{g_{v_t}}{\frac{f_t}{n_t}} = \left[\begin{array}{c} e_2\left[\frac{(1-\lambda_1-\lambda_2)v_t+\lambda_1 q_t^1 v_t+\lambda_2 q_t^2 v_t}{n_t}\right]^{\eta_2-1}\left[(1-\lambda_1-\lambda_2)+\lambda_1 q_t^1+\lambda_2 q_t^2\right] \\ +e_{31}q_t^1\left(\frac{i_t}{k_t}\right)^{\eta_{31}}\left(\frac{q_t^1 v_t}{n_t}\right)^{\eta_{31}-1} \\ +e_{32}q_t^2\left(\frac{i_t}{k_t}\right)^{\eta_{32}}\left(\frac{q_t^2 v_t}{n_t}\right)^{\eta_{32}-1} \end{array}\right] \tag{67}$$

Use the FOC and the estimates of Table 1 whereby $\eta_1 = \eta_2 = 2$ and $\eta_{31} = \eta_{32} = 1$ to solve for the asset values and the decision variables, one gets:

For capital and investment,

$$\begin{aligned} \frac{Q_t^K}{(1-\tau_t)\frac{f_t}{k_t}} &= \left(\left[e_1(\frac{i_t}{k_t}) + e_{31}\left(\frac{q_t^1 v_t}{n_t}\right) + e_{32}\left(\frac{q_t^2 v_t}{n_t}\right)\right] + \frac{p_t^I}{\frac{f_t}{k_t}}\right) \\ \frac{i_t}{k_t} &= \frac{1}{e_1}\left[\frac{Q_t^K}{(1-\tau_t)\frac{f_t}{k_t}} - \frac{p_t^I}{\frac{f_t}{k_t}} - \left[e_{31}\left(\frac{q_t^1 v_t}{n_t}\right) + e_{32}\left(\frac{q_t^2 v_t}{n_t}\right)\right]\right] \end{aligned} \tag{68}$$

For labor and hiring,

$$\begin{aligned} \frac{Q_t^N}{(1-\tau_t)\frac{f_t}{n_t}} &= \frac{\left[\begin{array}{c} e_2\frac{v_t}{n_t}\left[(1-\lambda_1-\lambda_2)+\lambda_1 q_t^1+\lambda_2 q_t^2\right]^2 \\ +e_{31}q_t^1\left(\frac{i_t}{k_t}\right) + e_{32}q_t^2\left(\frac{i_t}{k_t}\right) \end{array}\right]}{q_t} \\ \frac{v_t}{n_t} &= \frac{1}{e_2\left[(1-\lambda_1-\lambda_2)+\lambda_1 q_t^1+\lambda_2 q_t^2\right]^2}\left[\frac{Q_t^N}{(1-\tau_t)\frac{f_t}{n_t}} - e_{31}q_t^1\left(\frac{i_t}{k_t}\right) - e_{32}q_t^2\left(\frac{i_t}{k_t}\right)\right] \end{aligned} \tag{69}$$

Denote:

$$\begin{aligned}\Lambda_t &\equiv (1-\lambda_1-\lambda_2)+\lambda_1 q_t^1+\lambda_2 q_t^2 \\ \Omega_t &= e_{31}q_t^1+e_{32}q_t^2\end{aligned} \tag{70}$$

Thus:

$$\frac{i_t}{k_t}=\frac{1}{e_1}\left[\frac{Q_t^K}{(1-\tau_t)\frac{f_t}{k_t}}-\frac{p_t^I}{\frac{f_t}{k_t}}-\Omega_t\frac{v_t}{n_t}\right] \tag{71}$$

$$\frac{v_t}{n_t}=\frac{1}{e_2\Lambda_t^2}\left[q_t\frac{Q_t^N}{(1-\tau_t)\frac{f_t}{n_t}}-\Omega_t\frac{i_t}{k_t}\right] \tag{72}$$

Therefore:

$$\begin{aligned}\frac{i_t}{k_t} &= \frac{1}{e_1}\left[\frac{Q_t^K}{(1-\tau_t)\frac{f_t}{k_t}}-\frac{p_t^I}{\frac{f_t}{k_t}}-\Omega_t\left[\frac{1}{e_2\Lambda_t^2}\left[q_t\frac{Q_t^N}{(1-\tau_t)\frac{f_t}{n_t}}-\Omega_t\frac{i_t}{k_t}\right]\right]\right] \\ \frac{i_t}{k_t}\left[e_1-\frac{\Omega_t^2}{e_2\Lambda_t^2})\right] &= \left[\frac{Q_t^K}{(1-\tau_t)\frac{f_t}{k_t}}-\frac{p_t^I}{\frac{f_t}{k_t}}-\Omega_t\left[\frac{1}{e_2\Lambda_t^2}\frac{q_tQ_t^N}{(1-\tau_t)\frac{f_t}{n_t}}\right]\right] \\ \frac{i_t}{k_t} &= \left(\frac{e_1e_2\Lambda_t^2-\Omega_t^2}{e_2\Lambda_t^2}\right)^{-1}\left[\frac{Q_t^K}{(1-\tau_t)\frac{f_t}{k_t}}-\frac{p_t^I}{\frac{f_t}{k_t}}-q_t\Omega_t\left[\frac{1}{e_2\Lambda_t^2}\frac{Q_t^N}{(1-\tau_t)\frac{f_t}{n_t}}\right]\right] \\ &= \frac{1}{e_1e_2\Lambda_t^2-\Omega_t^2}\left[e_2\Lambda_t^2\left(\frac{Q_t^K}{(1-\tau_t)\frac{f_t}{k_t}}-\frac{p_t^I}{\frac{f_t}{k_t}}\right)-q_t\Omega_t\frac{Q_t^N}{(1-\tau_t)\frac{f_t}{n_t}}\right]\end{aligned} \tag{73}$$

where I have used

$$\begin{aligned}\frac{Q_t^K}{(1-\tau_t)\frac{f_t}{k_t}} &= \left(\frac{g_{i_t}}{\frac{f_t}{k_t}}+\frac{p_t^I}{\frac{f_t}{k_t}}\right) \\ \frac{g_{i_t}}{\frac{f_t}{k_t}} &= \frac{Q_t^K}{(1-\tau_t)\frac{f_t}{k_t}}-\frac{p_t^I}{\frac{f_t}{k_t}}\end{aligned}$$

Similarly for vacancy creation:

$$\begin{aligned}\frac{v_t}{n_t} &= \frac{1}{e_2\Lambda_t^2}\left[q_t\frac{Q_t^N}{(1-\tau_t)\frac{f_t}{n_t}}-\Omega_t\frac{1}{e_1}\left[\frac{Q_t^K}{(1-\tau_t)\frac{f_t}{k_t}}-\frac{p_t^I}{\frac{f_t}{k_t}}-\Omega_t\frac{v_t}{n_t}\right]\right] \\ &= \frac{1}{e_1e_2\Lambda_t^2-\Omega_t^2}\left[e_1q_t\frac{Q_t^N}{(1-\tau_t)\frac{f_t}{n_t}}-\Omega_t\left(\frac{Q_t^K}{(1-\tau_t)\frac{f_t}{k_t}}-\frac{p_t^I}{\frac{f_t}{k_t}}\right)\right]\end{aligned} \tag{74}$$

13.2 Elasticities

Given the above equations it is possible to solve for the investment and vacancy rates and the relevant elasticities.

13.2.1 Investment

$$\frac{i_t}{k_t} = \frac{1}{e_1 e_2 \Lambda_t^2 - \Omega_t^2} \left[e_2 \Lambda_t^2 \left(\frac{Q_t^K}{(1-\tau_t)\frac{f_t}{k_t}} - \frac{p_t^I}{\frac{f_t}{k_t}} \right) - q_t \Omega_t \frac{Q_t^N}{(1-\tau_t)\frac{f_t}{n_t}} \right] \tag{75}$$

$$\frac{\partial \frac{i_t}{k_t}}{\partial \frac{Q_t^K}{(1-\tau_t)\frac{f_t}{k_t}}} = \frac{e_2 \Lambda_t^2}{e_1 e_2 \Lambda_t^2 - \Omega_t^2} > 0 \tag{76}$$

$$\frac{\partial \frac{i_t}{k_t}}{\partial \frac{Q_t^N}{(1-\tau_t)\frac{f_t}{n_t}}} = \frac{-q_t \Omega_t}{e_1 e_2 \Lambda_t^2 - \Omega_t^2} > 0 \tag{77}$$

$$\frac{\partial \frac{i_t}{k_t}}{\partial \frac{p_t^I}{\frac{f_t}{k_t}}} = -\frac{e_2 \Lambda_t^2}{e_1 e_2 \Lambda_t^2 - \Omega_t^2} < 0 \tag{78}$$

The estimates of Table 1 indicate that $e_1 e_2 \Lambda_t^2 - \Omega_t^2 > 0$ and that $\Omega_t < 0$.
Hence $\frac{i_t}{k_t}$ is a positive function of $\frac{Q_t^K}{(1-\tau_t)\frac{f_t}{k_t}}$ and $\frac{Q_t^N}{(1-\tau_t)\frac{f_t}{n_t}}$ and a negative function of $\frac{p_t^I}{\frac{f_t}{k_t}}$.
Going to job filling rates:

$$\frac{i_t}{k_t} = \frac{e_2 \left[(1-\lambda_1-\lambda_2) + \lambda_1 q_t^1 + \lambda_2 q_t^2 \right]^2 P_t^K - (q_t^1 + q_t^2) \left[e_{31} q_t^1 + e_{32} q_t^2 \right] P_t^N}{e_1 e_2 \left[(1-\lambda_1-\lambda_2) + \lambda_1 q_t^1 + \lambda_2 q_t^2 \right]^2 - \left[e_{31} q_t^1 + e_{32} q_t^2 \right]^2} \tag{79}$$

where:

$$P_t^K \equiv \frac{\widetilde{Q}_t^K}{(1-\tau_t)\frac{f_t}{k_t}} > 0$$

$$P_t^N \equiv \frac{Q_t^N}{(1-\tau_t)\frac{f_t}{n_t}} > 0$$

Hence:

$$\frac{\partial \frac{i_t}{k_t}}{\partial q_t^1} = \frac{2e_2\lambda_1\Lambda_t P_t^K - P_t^N\left[2e_{31}q_t^1 + q_t^2(e_{31}+e_{32})\right]}{e_1e_2\Lambda_t^2 - \Omega_t^2} - \frac{\left[e_2\Lambda_t^2 P_t^K - \Omega_t q_t P_t^N\right]\left[2(e_1e_2\lambda_1\Lambda_t - e_{31}\Omega_t)\right]}{\left[e_1e_2\Lambda_t^2 - \Omega_t^2\right]^2} \tag{80}$$

$$\frac{\partial \frac{i_t}{k_t}}{\partial q_t^2} = \frac{2e_2\lambda_2\Lambda_t P_t^K - P_t^N\left[2e_{32}q_t^2 + q_t^1(e_{31}+e_{32})\right]}{e_1e_2\Lambda_t^2 - \Omega_t^2} - \frac{\left[e_2\Lambda_t^2 P_t^K - \Omega_t q_t P_t^N\right]\left[2(e_1e_2\lambda_2\Lambda_t - e_{32}\Omega_t)\right]}{\left[e_1e_2\Lambda_t^2 - \Omega_t^2\right]^2} \tag{81}$$

13.2.2 Vacancy Creation

$$\frac{v_t}{n_t} = \frac{1}{e_1e_2\Lambda_t^2 - \Omega_t^2}\left[e_1q_t\frac{Q_t^N}{(1-\tau_t)\frac{f_t}{n_t}} - \Omega_t\left(\frac{Q_t^K}{(1-\tau_t)\frac{f_t}{k_t}} - \frac{p_t^I}{\frac{f_t}{k_t}}\right)\right] \tag{82}$$

$$\frac{\partial \frac{v_t}{n_t}}{\partial \frac{Q_t^K}{(1-\tau_t)\frac{f_t}{k_t}}} = \frac{-\Omega_t}{e_1e_2\Lambda_t^2 - \Omega_t^2} > 0 \tag{83}$$

$$\frac{\partial \frac{v_t}{n_t}}{\partial \frac{Q_t^N}{(1-\tau_t)\frac{f_t}{n_t}}} = \frac{e_1q_t}{e_1e_2\Lambda_t^2 - \Omega_t^2} > 0 \tag{84}$$

$$\frac{\partial \frac{v_t}{n_t}}{\partial \frac{p_t^I}{\frac{f_t}{k_t}}} = \frac{\Omega_t}{e_1e_2\Lambda_t^2 - \Omega_t^2} < 0 \tag{85}$$

Hence $\frac{v_t}{n_t}$ is a positive function of $\frac{Q_t^K}{(1-\tau_t)\frac{f_t}{k_t}}$ and $\frac{Q_t^N}{(1-\tau_t)\frac{f_t}{n_t}}$,and a negative function of $\frac{p_t^I}{\frac{f_t}{k_t}}$. Going to job filling rates:

$$\frac{v_t}{n_t} = \frac{\left[e_1\left(q_t^1+q_t^2\right)P_t^N - \left[e_{31}q_t^1 + e_{32}q_t^2\right]P_t^K\right]}{e_1e_2\left[(1-\lambda_1-\lambda_2) + \lambda_1q_t^1 + \lambda_2q_t^2\right]^2 - \left[e_{31}q_t^1 + e_{32}q_t^2\right]^2} \tag{86}$$

and so:

$$\frac{\partial \frac{v_t}{n_t}}{\partial q_t^1} = \frac{e_1P_t^N - e_{31}P_t^K}{e_1e_2\Lambda_t^2 - \Omega_t^2} - \frac{\left[e_1q_tP_t^N - \Omega_tP_t^K\right]\left[2e_1e_2\lambda_1\Lambda_t - 2e_{31}\Omega_t\right]}{\left[e_1e_2\Lambda_t^2 - \Omega_t^2\right]^2} \tag{87}$$

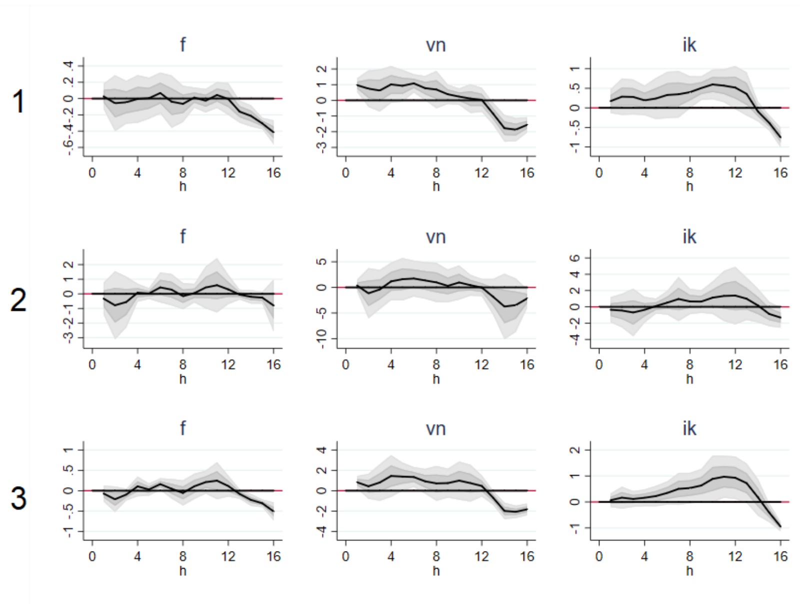
$$\frac{\partial \frac{v_t}{n_t}}{\partial q_t^2} = \frac{e_1P_t^N - e_{32}P_t^K}{e_1e_2\Lambda_t^2 - \Omega_t^2} - \frac{\left[e_1q_tP_t^N - \Omega_tP_t^K\right]\left[2e_1e_2\lambda_2\Lambda_t - 2e_{32}\Omega_t\right]}{\left[e_1e_2\Lambda_t^2 - \Omega_t^2\right]^2} \tag{88}$$

14 Appendix E: Alternative Predictors

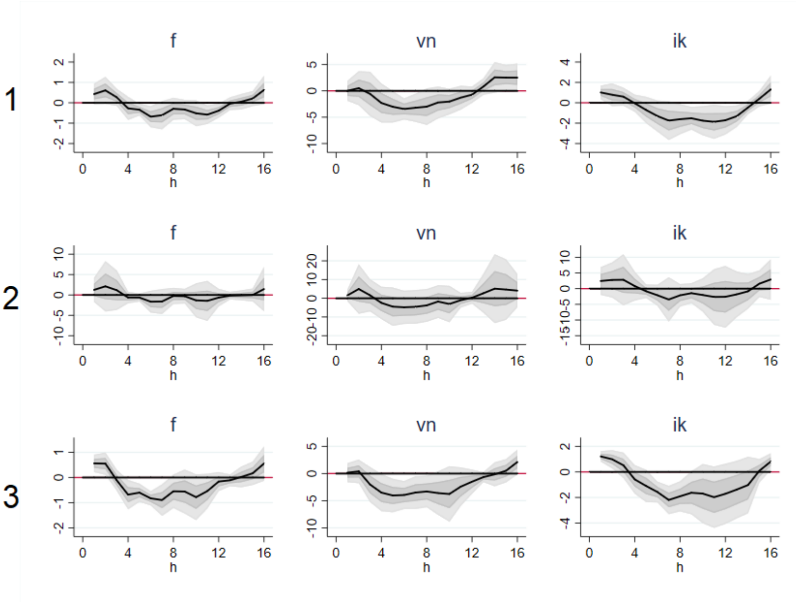
This Appendix examines the question whether predictions of GDP, vacancy rates, and investment rates can be generated by using the observed decision variables themselves, i.e., vacancy rates and investment rates, as well as the relative price of investment, as the predictors rather than using asset values. Figure E-1 reports the IRFs in the same format as Figure 1, but now using the variables $\widehat{D_{j,t}}$ rather than the asset values, where $D_{j,t} \in \{\frac{i_t}{k_t}, \frac{v_t}{n_t}, \frac{p_t^I}{\frac{f_t}{k_t}}\}$.

Figure E-1

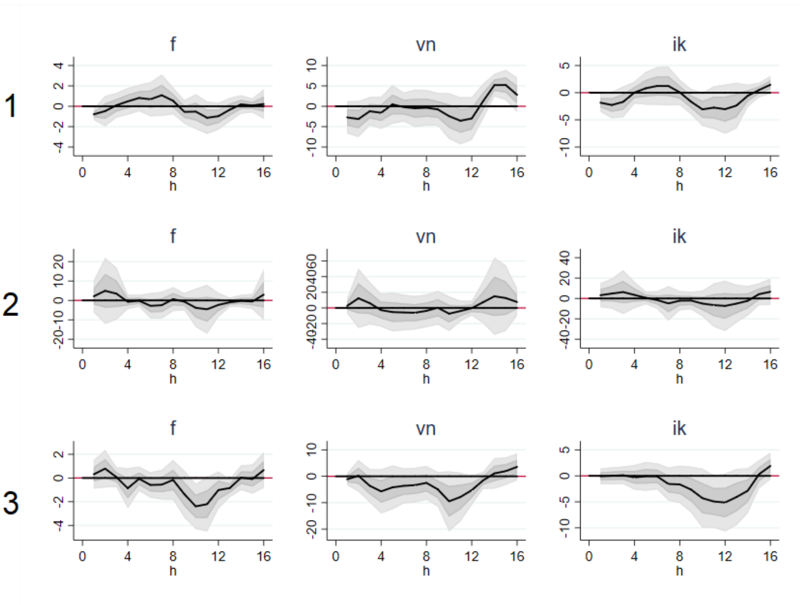
LP-IV Projections of f_{t+h}, $\frac{v_{t+h}}{n_{t+h}}$, $\frac{i_{t+h}}{k_{t+h}}$ Using the Decision Variables and the Relative Price of Capital as Predictors



a. Impulse Response Functions of f_{t+h}, $\frac{v_{t+h}}{n_{t+h}}$, and $\frac{i_{t+h}}{k_{t+h}}$ using $\widehat{\frac{v_t}{n_t}}$



b. Impulse Response Functions of f_{t+h}, $\frac{v_{t+h}}{n_{t+h}}$, and $\frac{i_{t+h}}{k_{t+h}}$ using $\widehat{\frac{i_{tt}}{k_t}}$



c. Impulse Response Functions of f_{t+h}, $\frac{v_{t+h}}{n_{t+h}}$, and $\frac{i_{t+h}}{k_{t+h}}$ using $\widehat{\frac{p^I_t}{\frac{f_t}{k_t}}}$

The results in the figure do not indicate consistent predictive ability. The price of investment $\frac{p^I_t}{\frac{f_t}{k_t}}$ and the investment rate have very diverse effects across specifications on all three variables, including sign switches. Vacancy rates also have contradictory effects, including counter-intuitive results, whereby GDP falls as vacancy rates rise. Importantly, the confidence bands indicate that the results are often insignificant.