Capital Reallocation and Liquidity*

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Abstract

This paper studies the cyclical properties of capital reallocation and capital liquidity. We show that the amount of capital reallocation and the benefits to reallocation vary at the business cycle frequency. The amount of capital reallocation is procyclical. In contrast, the benefits to capital reallocation appear countercyclical. We measure the amount of reallocation using data on gross flows of capital and the benefits to capital reallocation using the cross sectional dispersion of total factor productivity, capacity utilization, and Tobin's q. We study a calibrated model of an economy where capital reallocation is costly and impute the cost of reallocation which is consistent with the amount of reallocation in the data. We find that the cost of reallocation needs to vary countercyclically to generate the observed joint cyclical properties of reallocation and dispersion. The cyclical variation in this cost is interpreted as variation in the liquidity of capital.

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1 Introduction

How does capital reallocation and capital liquidity vary over the business cycle? This paper presents evidence that the amount of capital reallocation is procyclical while the benefits to capital reallocation are countercyclical. We use a calibrated model of costly capital reallocation to show that the liquidity process which reconciles the empirical amount of capital reallocation with the associated benefits is procyclical.

First, we measure the amount of capital reallocation using data on sales of plant, property and equipment, acquisitions and existing home sales. Then, we measure the benefits to reallocation using data on the cross industry variation in total factor productivity growth rates, the cross industry variation in capacity utilization and the cross sectional variation in firm level values of Tobin's q. We document the cyclical properties of both the amount of and benefits to reallocation. The amount of reallocation is highly positively correlated with GDP at the business cycle frequency; however the benefits to reallocation are not. In fact, our measures suggest that the benefits to reallocation are countercyclical. This implies that the cost which generates the observed cyclical properties of capital reallocation is countercyclical. We interpret the cyclical variation in this cost as cyclical variation in "liquidity"; liquidity is hence procyclical.

The focus on frictions which vary at a business cycle frequency is not new. Models such as Bernanke and Gertler (1989), Kiyotaki and Moore (1997) and Rampini (2000), for example, generate countercyclical agency costs which can be interpreted as a form of liquidity. However, this literature focuses on the effect of frictions on investment or on the net flow of capital. In contrast this paper studies gross flows of capital and focuses on the market for used capital. Shleifer and Vishny (1992) and Eisfeldt (2002) also focus on secondary markets for capital but are not quantitative. In this paper, since the process for liquidity is imputed, we avoid the problem of measuring difficult objects like the level of agency costs or the amount of adverse selection.

The effects of heterogeneity across firms on investment has been studied by Hopenhayn (1992), Bertola and Caballero (1994), and Monge (2001), among others. We build on the model of Ramey and Shapiro (1998) who study capital reallocation due to sectoral shocks and show how idiosyncratic or industry shocks can affect the aggregate economy. We also build on work by Jovanovic and Rousseau (2002) who develop a theory of mergers as profitable reallocation due to dispersion in q and show that many merger waves coincide with an increase in the dispersion of q.

This paper also compares the cyclical properties of capital reallocation to those of labor reallocation.[1] Davis, Haltiwanger and Schuh (1996) document the countercyclical nature of gross job flows. However, we show that gross job flows, like gross capital flows, are procyclical, although weakly so, when net changes in employment are excluded. This is consistent with the complementarity of capital and labor in most production functions.

The paper proceeds as follows. Section 2 provides an empirical characterization of the business cycle properties of reallocation. We discuss the cyclical properties of the reallocation of capital, the reallocation of labor, and the benefits to reallocation. Section 3 presents the model, which is calibrated and simulated in Section 4, where we also discuss the implied business cycle properties of liquidity. Section 5 discusses possible explanations for the variation in the cost of reallocation with aggregate conditions. Section 6 concludes.

2 Business Cycle Properties of Reallocation

2.1 Reallocation of Capital

In this section, we document the cyclical properties of the amount of and benefits to capital reallocation. We use three series to measure capital reallocation: existing home sales, sales of plant, property and equipment and acquisitions.[2] A detailed description of the data we use throughout the paper is in the Appendix. Ideally, we would like to use data on all reallocation of capital across households and firms, of which these three measures are only a subset. We will underestimate the level of reallocation, so to account for this we will also look at turnover rates, or reallocation normalized by the subset of the capital stock included in our data. We hope that by using these three different measures, we can get a broader characterization of the variation in reallocation.

To study the cyclical properties of reallocation, we use the Hodrick-Prescott filter described in Hodrick and Prescott (1980) to extract the cyclical

[1] See Caballero and Hammour (1999) and (2000) for earlier studies in a similar spirit.

[2] The data on existing home sales were gathered from the National Association of Realtors. The data on sales of plant property and equipment and acquisitions are from COMPUSTAT. See the data appendix for details on how the series were constructed.

component of the log series'.[3] We compare the cyclical properties of the reallocation series to that of log GDP and also plot the series against NBER recession dates. Table 2 presents the correlation of output with our measures of capital reallocation. We will focus on the HP filtered log series, but report statistics for linearly detrended data as well as for turnover rates. The correlation of capital reallocation and output is highly positive. For both existing home sales and acquisitions it is around 0.6. For sales of plant, property and equipment it is about 0.2. Figure 1 plots the cyclical components of the capital reallocation series against that of GDP. The procyclical nature of capital reallocation shows up clearly in the graph; all series appear to move together and to comove with GDP. Moreover, NBER recession dates are associated with considerable drops in the level of capital reallocation. Figure 2 plots the cyclical components of the capital reallocation turnover series against GDP, and replicates the features of the first plot.

We conclude that capital reallocation is procyclical. Interestingly, the focus of most of the finance and real estate economics literature seems to be on the correlation between volume and prices or returns in financial markets and housing markets, respectively, rather than aggregate fundamentals like GDP or employment (see, e.g., Lo and Wang (2000) and Stein (1995) and the papers cited therein). The finding in both the finance and real estate literature is that the correlation between volume and prices or returns, and hence good times, is positive. This is consistent with our finding for capital reallocation.

2.2 Reallocation of Labor

It is interesting to compare our results for the cyclical properties of capital reallocation to the results of the literature on job reallocation (see, e.g., Davis, Haltiwanger, and Schuh (1996)). This literature has focused on the fact that job reallocation as measured by gross job flows, which are the sum of gross job creation and gross job destruction, is countercyclical.[4] Using their data we show that the correlation of the Hodrick-Prescott filtered job reallocation rate and the cyclical component of GDP is -0.89, and that the

[3]To extract the cyclical component from annual data we use a weight of 100 in the filter.

[4]Caballero and Hammour (1999) challenge this conclusion and argue that recessions reduce cumulative reallocation. Their result seems closely related to our finding that excess reallocation is procyclical (see below).

correlation with the cyclical component of the net change in employment, which is the correlation that Davis, Haltiwanger, and Schuh (1996) focus on, is -0.52. This confirms the result in the literature (see Table 3).

In contrast, we find that gross job flows excluding net changes in employment are (weakly) procyclical and the correlation with detrended GDP is 0.01. In fact, the correlation of excess job reallocation with the detrended net change in employment is 0.28. Davis, Haltiwanger, and Schuh (1996) call this measure excess job reallocation since it measures the amount of simultaneous creation and destruction of jobs.[5] This measure corresponds more closely to our measures of the reallocation of used capital since our measures explicitly do not include net investment. From this vantage point, a consistent picture of the cyclical properties of reallocation of labor and capital emerges: the reallocation of labor, like the reallocation of capital, is procyclical, although not as strongly so.

While the results on the procyclicality of excess job reallocation have, to the best of our knowledge, not been stressed in the literature, it is well known that quits are procyclical (see, e.g., Akerlof, Rose, and Yellen (1998)). The two results may be related if workers who quit do so to take other jobs rather than to drop out of employment.

2.3 Benefits to Reallocation

In this subsection we provide several measures of the benefits to reallocation. First, we present three of our own measures of the benefits to reallocation: the dispersion of total factor productivity across industries, the dispersion of capacity utilization rates across industries, and the dispersion of Tobin's q across firms. In addition, we discuss measures of "reallocation shocks" studied in the literature.

First, we document the cyclical properties of the dispersion of total factor productivity (TFP) growth rates across industries. The idea is that capital should be reallocated to sectors with higher TFP growth and away from sectors with lower TFP growth and thus we expect the benefits to reallocation to be high when the dispersion of TFP growth rates is high. We use two alternative measures of the cross-sectional dispersion of productivity growth rates. The first measure computes the time series of the sectoral-output

[5] Davis, Haltiwanger, and Schuh (1996) do not study the cyclical properties of excess job reallocation.

weighted standard deviation of "multifactor productivity" growth rates (from the Bureau of Labor Statistics) across 18 durable and non-durable manufacturing industries at the two digit SIC code level. The correlation between the cyclical component of sectoral TFP growth dispersion and the cyclical component of GDP is -0.463 (see Panel A of Table 4). The second measure computes the time series of the sectoral value-added weighted standard deviation of "productivity changes" adjusted for variation in capacity utilization (from Basu, Fernald, and Kimball (2001)) across 29 manufacturing and non-manufacturing industries at roughly the two digit SIC code level within manufacturing and the one digit SIC code level outside manufacturing.[6] The correlation between the cyclical component of sectoral dispersion in productivity changes and the cyclical component of GDP is -0.437 (see Panel A of Table 4). Thus, the dispersion of productivity according to both measures is countercyclical which suggests countercyclical benefits to reallocation. Figure 4 plots the cyclical component of the standard deviation of TFP growth rates across industries. The negative correlation is evident from the graph.

A second measure of the benefits to reallocation we propose is the dispersion of capacity utilization across sectors. A high dispersion of capacity utilization rates suggests that the benefits to reallocating capital are high. We use the sectoral-output weighted standard deviation of capacity utilization rates (from the Federal Reserve Board) across 16 durable and non-durable manufacturing industries at the two digit SIC code level as our measure of the dispersion of capacity utilization rates. The correlation between the cyclical component of sectoral capacity utilization dispersion and the cyclical component of GDP is -0.672 (see Panel B of Table 4). The dispersion of capacity utilization is hence countercyclical which, consistent with the results above, suggests countercyclical benefits to reallocation.

Finally, we study the cyclical properties of the benefits to reallocation using data on the dispersion in firm level q. According to q theory, capital should flow from firms with low q's to firms with high q's. The higher the dispersion in q, the more the economy can benefit from reallocation. Panel C in Table 4 reports the correlation between the cyclical component of q dispersion and GDP. Firm level q is computed as the market to book ratio for the firm's total assets. A detailed description of the data we use throughout the paper is in the Appendix. We use four measures of the dispersion in q:

[6] We thank John Fernald for providing us with their estimates of industry productivity changes.

the standard deviation of q's less than 5, the standard deviation of q's less than 10, the standard deviation of q, and the difference between the third and first quartiles of q normalized by the median q. Concern about measurement error led us to exclude extreme values of q in the first two measures. Using an upper bound to exclude high q's likely subject to measurement error may bias the variation in the measured standard deviation.[7] For this reason we also report dispersion using quartile differences. The correlation of the cyclical components of dispersion in q and GDP varies quite a bit depending on the measure, from -0.13 to 0.19. Although dispersion is measured with error, we can observe that the correlation is less strongly positive than that of capital reallocation. In fact, the dispersion of q seems essentially acyclical given the standard errors of our estimates.

The literature has studied the dispersion of employment growth rates across industries and the dispersion of industry index returns and industry index excess returns across industries as measures of sectoral shocks. Lilien (1982) finds that there is a positive correlation between the aggregate unemployment rate and the standard deviation of employment growth rates across industries in annual postwar U.S. data. Relatedly, Abraham and Katz (1986) document that the correlation between the dispersion of employment growth rates across industries and the volume of help wanted advertising is negative. Loungani, Rush, and Tave (1990) find a positive correlation between the aggregate unemployment rate and (up to three lags of) stock return dispersion measures across industries in annual U.S. data. They use both the equally weighted and the employment weighted cross-sectional standard deviation of S&P industry index returns as measures of stock return dispersion. Brainard and Cutler (1993) find that the employment-weighted variance of excess returns across industries is positively correlated with unemployment in quarterly U.S. data. They also report that they obtain similar results using the value-weighted variance of excess returns across firms, but these results are not presented in the published version of the paper. To sum up, the various measures of cross-sectional dispersion studied in the literature are consistent with countercyclical dispersion or reallocation shocks.

[7] Negative q's were always excluded.

3 Model

We develop a model where capital reallocation is an important feature of the economy in equilibrium. Reallocation of capital between firms is driven by idiosyncratic shocks to firm level productivity. Since we are interested in the business cycle properties of reallocation and liquidity, the economy will also be subject to aggregate productivity shocks.

To solve the model, we study the problem of a social planner who allocates the economy's capital amongst firms or technologies and maximizes the expected utility of the representative agent subject to the aggregate resource constraint. The representative agent has standard preferences

$$E\left[\sum_{t=0}^{\infty}\beta^t u(C_t)\right] \tag{1}$$

where $u(C) = \frac{C^{1-\sigma}}{1-\sigma}$, $\beta < 1$, and $\sigma > 0$.

The economy has two technologies. We assume that capital is technology specific but can be reallocated from one technology to the other. However, capital is illiquid which means that reallocation is costly and illiquidity may vary with the state of the economy. In addition, we assume that there are adjustment costs for capital and that investment is partially irreversible. Disinvestment is most likely to occur through redeployment of capital in an alternative use instead of by transforming capital goods back into consumption goods. Partial irreversibility combined with opportunities for reallocation captures this idea.

Denote the beginning of period capital stock in technology i by $K_{i,t}$ and the capital stock after reallocation by $\hat{K}_{i,t}$. We assume that reallocation, $R_{1\to 2,t}$ and $R_{2\to 1,t}$ occurs at the beginning of the period after the productivity of the two technologies have been realized and is instantaneous. Thus, it is the capital stock after reallocation which is used for production in period t. Reallocation is assumed to be instantaneous in order to capture the idea that increasing the capital stock by reallocating capital is faster than through investment. This is an important difference to Ramey and Shapiro (1998). They assume that capital reallocated at time t becomes available only at time $t+1$ and cannot be deployed in production at time t. This means that reallocation is much more costly than in our model and implies that only large shocks, such as the military buildup that they consider, trigger capital reallocation. In contrast, in our model reallocation of capital occurs most of the time.

The resource constraint for the model economy is:

$$C_t \leq \sum_{i=1}^{2} A_{i,t} F(\hat{K}_{i,t}) - I_{i,t} - \Gamma_I(I_{i,t}, \hat{K}_{i,t}). \qquad (2)$$

The production function is $F(K_i) = K_i^\alpha$, $\forall i$. The law of motion for capital, for all i and $i \neq j$, is:

$$\begin{aligned} \hat{K}_{i,t} &= K_{i,t} + R_{j\to i,t} - R_{i\to j,t} - \Gamma_R(R_{i\to j,t}, K_{i,t}) \\ K_{i,t+1} &= (1-\delta)\hat{K}_{i,t} + I_{i,t}. \end{aligned} \qquad (3)$$

where $R_{i\to j,t} \geq 0$. The functions

$$\begin{aligned} \Gamma_I(I_{i,t}, \hat{K}_{i,t}) &\equiv \frac{\gamma_{I^+}}{2}\left(\frac{I^+_{i,t}}{\hat{K}_{i,t}}\right)^2 \hat{K}_{i,t} + \frac{\gamma_{I^-}}{2}\left(\frac{I^-_{i,t}}{\hat{K}_{i,t}}\right)^2 \hat{K}_{i,t} \\ \Gamma_R(R_{i\to j,t}, K_{i,t}) &\equiv \frac{\gamma_R}{2}\left(\frac{R_{i\to j,t}}{K_{i,t}}\right)^2 K_{i,t}, \end{aligned}$$

with $I^+ \equiv \max\{I, 0\}$, $I^- \equiv \min\{I, 0\}$, $\gamma_R, \gamma_I^+, \gamma_I^- \geq 0$, and $\gamma_I^- >> \gamma_R$, describe the investment adjustment costs, partial investment irreversibility and the discount incurred when capital is reallocated. Notice that we assume a standard quadratic adjustment cost function which is linearly homogenous in investment and the capital stock (see Abel and Eberly (1994)). Similarly, the illiquidity of capital is modeled by assuming a quadratic reallocation cost function which is also linearly homogenous.

Fluctuations are driven by the productivity processes $A_{1,t}$ and $A_{2,t}$ which are modeled as follows. The two technologies are assumed to be symmetric. Productivity of technology i is the sum of an aggregate productivity shock, A^g, and a technology specific productivity shock, A_i^s, that is,

$$A_{i,t} = A_t^g + A_{i,t}^s.$$

We assume that $A_{i,t}^s = -A_{j,t}^s$, $i \neq j$, which means that the technology specific shocks are perfectly negatively correlated. Furthermore, we assume that aggregate productivity and technology specific productivity are independent and both follow a Markov chain.

Since we are interested in the effect of changes in illiquidity or the cost of reallocation as a function of the aggregate state of the economy, we will also consider an economy in which γ_R is a function of aggregate productivity, i.e., $\gamma_R(A_t^g)$.

4 Implied Business Cycle Properties of Liquidity

4.1 Calibration

The model is calibrated to annual data using standard values for preferences ($\beta = 0.96$ and $\sigma = 2$) and technology ($\alpha = 0.333$ and $\delta = 0.1$). Aggregate productivity and technology specific productivity are assumed to follow a two state Markov chain. Specifically, we assume that $A^g \in \{1 + \Delta^g, 1 - \Delta^g\}$ with $\Delta^g = 0.02$ and $A_i^s \in \{+\Delta^s, -\Delta^s\}$ with $\Delta^s = 0.1$. We assume that both productivity processes are described by the same Markov transition matrix

$$\Pi = \begin{bmatrix} \pi_{11} & 1 - \pi_{11} \\ 1 - \pi_{22} & \pi_{22} \end{bmatrix}$$

with $\pi_{11} = \pi_{22} = 0.75$.

The parameters of the adjustment cost function are $\gamma_{I^+} = 0.5$ and $\gamma_{I^-} = 10$ such that investment is effectively irreversible. We set the parameter for the cost of reallocation $\gamma_R = 0.5$. For the case where illiquidity varies with aggregate productivity we assume that γ_R is low (high) when aggregate productivity is high (low). Specifically, we assume that $\gamma_R \in \{0.5 + \lambda, 0.5 - \lambda\}$ and follows a Markov processes which is perfectly negatively correlated with the process for aggregate productivity. Setting the liquidity variation parameter $\lambda = 0$ recovers the case of constant illiquidity. We will consider three values for λ: 0, 0.2 and 0.4. Notice also that given this parameterization the unconditional expected illiquidity is held constant independent of λ.

The parameterization is summarized in Table 5.

4.2 Simulation Results

To match the empirical cyclical properties of reallocation, the model should generate reallocation which is positively correlated with output. We are interested in describing the process for the cost of reallocation, or illiquidity, which leads to increased reallocation when output is high. First, we report the moments of an economy with constant illiquidity. The simulation results are presented in Table 6. The constant illiquidity economy corresponds to $\lambda = 0$.

The model is calibrated to generate a positive average level of reallocation. About 1.6% of the capital stock is reallocated each period. The model is calibrated to an annual frequency, so each period corresponds to one year. As a comparison, empirically about 2% of plant, property and equipment was reallocated each year over the time period 1971 to 2000. In the model economy, reallocation contributes about 14% of total investment, the rest is due to new additions to the capital stock. Average plant property and equipment sales over the time period 1971 to 2000 are about 11% of average plant, property and equipment capital expenditures over the same period. Average reallocation is about the same in the high and low aggregate states when illiquidity is constant, while output is procyclical. The average reallocation discount incurred is about 1.3% of the average amount of reallocation and the average investment adjustment cost incurred is about 2.5% of the average amount of new investment.[8] Most importantly, the correlation between reallocation and output is near zero and in fact is slightly negative, in contrast to the empirical correlation documented in Table 2.

To generate procyclical capital reallocation, we modify the reallocation cost by varying illiquidity with the aggregate state. The illiquidity parameter γ_R in the reallocation cost function Γ_R varies countercyclically when a positive liquidity variation parameter, λ is introduced. In economies with positive λ, the discount incurred by reallocating capital is larger in the low aggregate state. The simulation results for $\lambda = 0.2$ appear in the second column of Table 6. With countercyclical reallocation costs, slightly more reallocation takes place on average. About 1.7% of the capital stock is reallocated each period and about 17% of total investment takes place through reallocation. Reallocation is about 22% above the unconditional average in the high aggregate state, and about 22% below average in the low state. The average reallocation discount and the average investment adjustment cost incurred do not change much from the constant illiquidity case. In fact, the average reallocation cost incurred does not vary with the aggregate state. Since the discount is larger in the low state, less reallocation occurs and as a result less costs are incurred. Countercyclical illiquidity generates procyclical reallocation. The correlation of reallocation and output is about 0.12 in logs, and 0.19 in levels.

Finally, when the liquidity variation parameter is increased to 0.4 the economy responds in a similar manner. The simulation results for this economy are presented in column 3 of Table 6. The main differences in the mo-

[8]As discussed above, the model is calibrated so that disinvestment occurs through reallocation and thus investment is always positive.

ments of this economy relative to those of the constant liquidity economy are an increased average amount of reallocation which is procyclical and covaries positively with output.

5 Discussion

The approach we have chosen here is to model the illiquidity or cost of reallocation directly as a physical cost and to argue that these frictions in capital reallocation need to be countercyclical to be consistent with the data. But why are the frictions in the market for used capital countercyclical? There does not seem to be a reason to believe that the physical cost of reallocating capital are countercyclical themselves. In addition, the opportunity cost of reallocation in terms of forgone production are presumably procyclical. Thus, we interpret the variation in the reallocation frictions implied by our reduced form model as variation in the endogenous frictions such as informational or contracting frictions.

That credit constraints vary with the business cycle and are countercyclical is well understood. However, most models in the literature explain countercyclical variation in the frictions in financing new investment rather than in the frictions in the reallocation of used capital. What countercyclical credit constraints imply for the amount of reallocation is not obvious. While in bad times potential buyers of used capital are more credit constrained and may hence be less able to buy, potential sellers of used capital may be more eager to sell since they are more credit constrained, too. Since capital reallocation is procyclical, we expect that the credit constraints of potential buyers vary more with aggregate conditions than those of sellers. Also, to the extent that the market for used capital is intermediated, countercyclical credit constraints of such intermediaries might explain countercyclical reallocation costs.

Furthermore, the amount of adverse selection in the market for used capital might vary countercyclically as in Eisfeldt (2002). In that model the amount of trade in the secondary market for projects is lower when productivity is lower despite the fact that the benefits to trading capital do not vary with productivity. This is due to the fact that when productivity is low, there are fewer "non-informational" reasons to trade and hence there is more adverse selection in bad times.

In our opinion, the countercyclical credit constraints and countercyclical adverse selection interpretation of the variation in reallocation costs is most convincing. There are, however, other possible explanations. First, there may be a "vintage capital" explanation for procyclical capital reallocation. Suppose that firms which make new investments sell their used capital to other firms. The amount of reallocation may then be procyclical simply because there is a lot of new investment when times are good. This explanation would however imply that firms which sell capital invest more which is not the case in our data. In fact, the mean (median) investment to plant, property & equipment ratio for firms which sell PP&E is 29% (21%) compared to 37% (25%) for firms which do not sell any PP&E. Thus, the vintage capital explanation does not seem to be consistent with the data at least for PP&E sales. This explanation may play a more important role in the housing data.

Second, if the capital of firms which exit is reallocated and firms which exit do not gradually sell off their capital (which we would observe) but rather are dropped from the sample, we may mismeasure the cyclical properties of reallocation since exits presumably are countercyclical. The problem is that we measure only sales of plant, property & equipment and do not have separate measures of purchases of used capital. As long as exiting firms are as likely to be sold as going concerns as continuing firms, the procyclical nature of acquisitions suggests that exits do not significantly change the properties of capital reallocation.

Third, Davis and Haltiwanger (1999) argue that an increase in dispersion in bad times may reduce the amount of new investment when investment involves sunk costs because of the value of waiting to invest. They argue that this option value effect reduces the creation of jobs in bad times when job destruction is high. Similarly, one might expect that if reallocation costs are sunk, increased volatility may decrease the amount of reallocation observed. It would be interesting to access if this effect can be quantitatively important in a calibrated model.

6 Conclusions

This paper documents the procyclical nature of the amount of capital reallocation and the contrasting countercyclical nature of the benefits to capital reallocation. In a frictionless economy or in an economy with time invariant frictions, one would expect more reallocation when the benefits to reallocating are higher. We use a calibrated model of costly capital reallocation to impute the countercyclical cost which reconciles these empirical observations. We interpret this state dependent cost of reallocating as "liquidity", broadly defined, and conclude that the liquidity of capital appears to be procyclical.

Appendix: Data Sources

Existing Home Sales Data: Existing single-family home sales are reported by the National Association of Realtors and are taken from Simmons, P., Ed., (2000), *Housing Statistics of the United States,* 3rd Edition, Lanham, MD, Bernan Press, and updated using the February 2002 issue of *Housing Market Statistics* published by the National Association of Home Builders. We use data from 1968 to 2000. Total housing units are from Simmons (2000). We use data from 1967 to 1999. The turnover rate is computed by dividing existing home sales for the year by the total housing units at the end of the previous year.

Acquisitions and Plant, Property and Equipment Sales Data: Acquisitions and sales of plant, property and equipment are reported in COMPUSTAT annual data items 129 and 107 and have been collected since 1971. The aggregate time series for acquisitions was created by summing over firms by year. Firm year observations in which the acquisitions entry contained a combined data code, were excluded. For the acquisitions to asset turnover rate, total assets were summed over firms by year using the same inclusion rule. The aggregate time series for sales of plant, property and equipment was created analogously as follows: Firm year observations in which the plant, property and equipment entry contained a combined data code, were excluded. For the plant, property and equipment turnover rate, total plant, property and equipment was summed over firms by year using the same inclusion rule.

Total Factor Productivity Data: The annual data on industry multifactor productivity and value of sectoral output is from the Bureau of Labor Statistics (http://www.bls.gov/). We use data for 18 durable and non-durable manufacturing industries at the two digit SIC code level (SIC 20, 22-30, 32-39) from 1963 to 1999. The standard deviation of productivity growth across sectors is computed by weighting the industries by the value of sectoral output at the end of the year.

Data on Productivity Changes Adjusted for Capacity Utilization: The annual data on industry productivity changes adjusted for variation in capacity utilization and value of sectoral value-added are from Basu, Fernald, and Kimball (2001). We use their estimates of productivity changes for 29 manufacturing and non-manufacturing industries at roughly the two digit SIC code level within manufacturing and the one digit SIC code level outside manufacturing from 1963 to 1989 which cover the entire non-farm, non-mining private economy. These estimates are adjusted for variation in capacity utilization using hours worked and are based on a dataset compiled by Dale Jorgenson and Barbara Fraumeni. See Basu, Fernald, and Kimball (2001) for details. The standard deviation of productivity changes across sectors is computed by weighting the industries by the value-added of the sector and productivity changes on a gross output basis are divided by 1 minus the materials to output ratio to obtain productivity changes on a value-added basis.

Capacity Utilization Data: The annual industry capacity utilization data is constructed from the monthly data provided by the Federal Reserve Board, Statistical Release G.17, (http://www.federalreserve.gov), by computing the average capacity utilization for the year in each industry. We use data for 16 durable and non-durable manufacturing industries at the two digit SIC code level (SIC 22-30, 32-36, 38-39) from 1967 to 1999. The standard deviation of capacity utilization across sectors is computed by weighting the industries by the value of sectoral output at the end of the year.

Tobin's q Data: The data used to compute the market to book ratios used to proxy for Tobin's q were collected from COMPUSTAT. The book value of assets is given by annual data item 6. The market value of assets was computed as the book value of assets (item 6) plus the market value of common stock less the sum of book value of common stock (item 60) and balance sheet deferred taxes (item 74). The series was constructed beginning in 1963, when COMPUSTAT began collecting the value of common stock. Firm year observations where total assets (item 6) were nonpositive, or where the book value of common stock (item 60) or deferred taxes (item 74) were negative, were excluded. Missing values for balance sheet deferred taxes were set to zero. For all dispersion calculations, firm year observations where computed q was negative were excluded. The standard deviation of q is computed using a market value weighting. The standard deviations of q's less than 10 and less than 5 are standard deviations of q weighted by market value for all q's less than the respective cutoff. Obvious cases of measurement error led us to introduce upper bounds for "reasonable" q's. We also computed weighted quartiles of q for all positive q's as a robustness check.

Job Flows Data: The annual data on the gross job creation rate and the gross job destruction rate from Davis, Haltiwanger and Schuh (1996) are from John Haltiwanger's web page at the University of Maryland. We used the updated series which includes data from 1973 through 1993. The timing of the data is as follows: the year t job creation or destruction rate refers to job creation or destruction between March 12, year $t-1$ and March 12, year t. When computing the contemporaneous correlation with (detrended) GDP we thus use GDP at the end of the first quarter of year t.

Macroeconomic Data: Annual and quarterly GDP data is from the FRED database at the Federal Reserve Bank in St. Louis (http://www.stls.frb.org/fred/). We use data from 1963 to 2000. NBER business cycle dates are from the National Bureau of Economic Research web page (http://www.nber.org/). We use the monthly dates in the figures.

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Table 1: Summary Statistics for Compustat Capital Reallocation Data

Level variables are in millions of dollars. Asset reallocation is used to abbreviate the sum of acquisitions plus sales PP&E. For the reallocation ratios in rows six to eleven, column four gives the ratio of the sample mean of the numerator to the sample mean of the denominator. If the numerator is a conditional variable, the denominator is computed using the same condition. The first three columns refer to sample statistics for firm level ratios.

Variable	Mean	Median	Standard Deviation	Ratio of Sample Means
Assets	1690.21	55.33	14287.36	n/a
Acquisitions	14.79	0	200.02	n/a
PP&E	337.65	9.32	2010.71	n/a
Sales of PP&E	7.62	0	145.77	n/a
Investment	62.98	1.86	493.13	n/a
$\frac{\text{Acquisitions}}{\text{Assets}}$	1.61%	0	0.18	0.88%
$\frac{\text{Acquisitions}}{\text{Assets}}\vert_{\text{acquiring}}$	8.48%	3.36%	0.43	3.86%
$\frac{\text{Sales of PP\&E}}{\text{PP\&E}}$	7.23%	0.13%	3.15	2.26%
$\frac{\text{Sales of PP\&E}}{\text{PP\&E}}\vert_{\text{selling}}$	13.45%	1.9%	4.3	3.53%
$\frac{\text{Asset Reallocation}}{\text{Investment}}$	n/a	2.37%	n/a	32.62%
$\frac{\text{Asset Reallocation}}{\text{Investment}}\vert_{\text{reallocating}}$	n/a	18.89%	n/a	47.94%
$\frac{\text{Asset Reallocation}}{\text{PP\&E}_{(t-1)}}$	31.60%	0.19%	12.80	6%
$\frac{\text{Asset Reallocation}}{\text{PP\&E}_{(t-1)}}\vert_{\text{reallocating}}$	58.48%	3.47%	17.40	9.47%
$\frac{\text{Asset Reallocation}}{\text{Assets}_{(t-1)}}$	8.82%	0.02%	23.57	1.17%
$\frac{\text{Asset Reallocation}}{\text{Assets}_{(t-1)}}\vert_{\text{reallocating}}$	17.12%	1.05%	32.84	3.21%
$\frac{\text{Sales of PP\&E}}{\text{Asset Reallocation}}$	37.22%	0	0.47	33.35%
$\frac{\text{Sales of PP\&E}}{\text{Asset Reallocation}}\vert_{\text{reallocating}}$	72.21%	100%	0.42	33.32%

Table 2: Reallocation of Capital

Deviations from trend are computed using the Hodrick and Prescott (1980) filter (HP) or a linear trend (LT). In the columns labeled 'Level' the natural logarithm of the level of each variable is used. In the columns label 'Turnover,' each variable is divided by a measure of the total stock to compute the turnover rate: Existing Home Sales are divided by a measure of the total housing units, Acquisitions and Acquisitions & PP&E Sales are divided by total assets and Plant, Property & Equipment Sales by total plant, property & equipment. Standard errors are corrected for heteroscedasticity and autocorrelation of the residuals à la Newey and West (1987) and are computed using a GMM approach adapted from the Hansen, Heaton, and Ogaki GAUSS programs. In panel B, the ratio of capital reallocation conditional on output above trend to capital reallocation conditional on output below trend is the ratio of the sum of reallocation over years where GDP is above trend to the sum of reallocation over years when GDP is below trend.

Panel A: Correlation of Output with Reallocation

Variable	Correlation of Output with			
	HP Level	LT Level	HP Turnover	LT Turnover
Existing Home Sales	0.614	0.489	0.605	0.507
	(0.204)	(0.271)	(0.195)	(0.240)
Acquisitions	0.633	0.319	0.584	0.409
	(0.141)	(0.285)	(0.133)	(0.211)
Plant, Property & Equipment Sales	0.211	0.271	0.232	0.382
	(0.203)	(0.286)	(0.161)	(0.194)
Acquisitions & PP&E Sales	0.599	0.341	0.584	0.421
	(0.142)	(0.298)	(0.139)	(0.210)

Panel B: Ratio of Capital Reallocation Conditional on Output Above Trend to Capital Reallocation Conditional on Output Below Trend

Variable	High/Low State Reallocation Ratio			
	HP Level	LT Level	HP Turnover	LT Turnover
Existing Home Sales	1.331	1.589	1.359	1.748
Acquisitions	1.907	1.759	1.966	1.726
Plant, Property & Equipment Sales	1.593	1.570	1.428	1.545

Table 3: Reallocation of Labor

Deviations from trend are computed using the Hodrick and Prescott (1980) filter (HP) or a linear trend (LT). Job Reallocation Rate is the sum of the annual gross job creation rate and annual gross job destruction rate from Davis, Haltiwanger, and Schuh (1996). Excess Job Reallocation Rate is job reallocation minus the net change in employment. Net Change in Employment is the difference between job creation and job destruction. Standard errors are corrected for heteroscedasticity and autocorrelation of the residuals à la Newey and West (1987) and are computed using a GMM approach adapted from the Hansen, Heaton, and Ogaki GAUSS programs.

	Correlation of Output with		Correlation of Net Change in Employment with	
Variable	HP	LT	HP	Not Detrended
Job Reallocation Rate	-0.890	-0.831	-0.515	-0.398
	(0.082)	(0.144)	(0.290)	(0.320)
Excess Job Reallocation Rate	0.011	0.021	0.280	0.258
	(0.327)	(0.355)	(0.348)	(0.408)

Table 4: Benefits to Reallocation

Deviations from trend are computed using the Hodrick and Prescott (1980) filter (HP) or a linear trend (LT). The time series of the (output-weighted) standard deviation of total factor productivity growth rates and capacity utilization across industries is computed using data from the Bureau of Labor Statistics (for 'multifactor productivity' and the value of sectoral production) and the Federal Reserve Board (for capacity utilization). We use data on durable and non-durable manufacturing industries at the two digit SIC code level. The time series of the (value-added weighted) standard deviation of productivity changes adjusted for variation in capacity utilization are from Basu, Fernald, and Kimball (2001). We use their estimates of productivity changes for manufacturing and non-manufacturing industries. See the Appendix for details. The time series of the (value-weighted) standard deviation of Tobin's q across firms is computed using data from COMPUSTAT excluding observations with values of q exceeding 5 and 10, respectively. Standard errors are corrected for heteroscedasticity and autocorrelation of the residuals à la Newey and West (1987) and are computed using a GMM approach adapted from the Hansen, Heaton, and Ogaki GAUSS programs.

Panel A: Dispersion in Total Factor Productivity

	Correlation of Output with	
Variable	HP	LT
Standard Deviation of TFP Growth Rates	-0.463	-0.129
	(0.202)	(0.259)
Standard Deviation of Productivity Changes	-0.437	-0.244
Adjusted for Capacity Utilization	(0.264)	(0.338)

Panel B: Dispersion in Capacity Utilization

	Correlation of Output with	
Variable	HP	LT
Standard Deviation of Capacity Utilization	-0.672	-0.560
	(0.204)	(0.261)

Panel C: Dispersion in Tobin's q

	Correlation of Output with	
Variable	HP	LT
Standard Deviation of Tobin's q ($q \leq 5$)	-0.130	-0.122
	(0.259)	(0.302)
Standard Deviation of Tobin's q ($q \leq 10$)	0.130	0.038
	(0.239)	(0.278)
Standard Deviation of Tobin's q	0.133	0.137
	(0.122)	(0.181)
Difference between 3rd and 1st Quartile	0.190	-0.017
Divided by the Median of Tobin's q	(0.266)	(0.296)

Table 5: Parameter Values for Calibration

Preferences					
		β	σ		
		0.96	2		
Technology					
α	δ	π_{11}	π_{22}	Δ^g	Δ^s
0.333	0.1	0.75	0.75	0.02	0.1
Adjustment Costs and Illiquidity					
	γ_{I^+}	γ_{I^-}	γ_R		
	0.5	10	0.5		

Table 6: Simulation Results

Liquidity Variation Parameter	$\lambda = 0$	$\lambda = 0.2$	$\lambda = 0.4$
Reallocation			
$E[R]$	0.1097	0.1144	0.1362
$E[R \mid A^g = 1 + \Delta^g]$	0.1109	0.1401	0.1993
$E[R \mid A^g = 1 - \Delta^g]$	0.1085	0.0888	0.0730
$E[R]/E[K_1 + K_2]$	0.0159	0.0166	0.0197
$E[R]/E[I_1 + I_2]$	0.1372	0.1657	0.1972
Investment			
$E[I]/E[K]$	0.1002	0.1002	0.1002
$E[I]$	0.6899	0.6905	0.6907
$E[I \mid A^g = 1 + \Delta^g]$	0.7421	0.7437	0.7439
$E[I \mid A^g = 1 - \Delta^g]$	0.6377	0.6374	0.6375
Capital			
$E[K]$	6.8864	6.8928	6.8963
$E[K \mid A^g = 1 + \Delta^g]$	6.9338	6.9411	6.9488
$E[K \mid A^g = 1 - \Delta^g]$	6.8390	6.8445	6.8478
Output			
$E[Y]$	3.0231	3.0242	3.0251
$E[Y \mid A^g = 1 + \Delta^g]$	3.0904	3.0922	3.0940
$E[Y \mid A^g = 1 - \Delta^g]$	2.9559	2.9561	2.9562
$\sigma(\ln(Y))$	0.0235	0.0238	0.0241
Consumption			
$E[C]$	2.3157	2.3161	2.3168
$\sigma(\ln(C))$	0.0190	0.0190	0.0191
Costs			
$E[\Gamma_R]/E[R]$	0.0128	0.0122	0.0088
$E[\Gamma_I]/E[I_1 + I_2]$	0.0254	0.0255	0.0255
Correlation of Reallocation and Output			
$\rho(\ln(R), \ln(Y))$	-0.0037	0.1246	0.2411
$\rho(R, Y)$	-0.0138	0.1915	0.3252

Figure 1: Capital Reallocation over the Cycle

Plotted series are the cyclical component of Hodrick-Prescott filtered log data normalized by standard deviation. Solid line denotes GDP, dash-dotted line denotes existing home sales, dashed line denotes acquisitions and dotted line denotes plant, property and equipment sales. Vertical lines denote NBER business cycle dates.

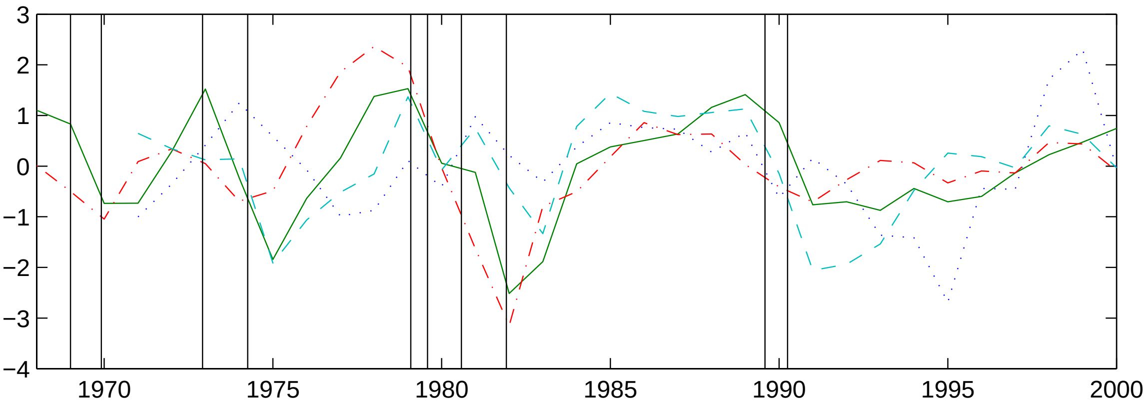

Figure 2: Turnover Rates of Capital over the Cycle

Plotted series are the cyclical component of Hodrick-Prescott filtered turnover rates normalized by standard deviation. Solid line denotes GDP, dash-dotted line denotes existing home sales divided by total housing units, dashed line denotes acquisitions divided by total assets and dotted line denotes plant, property and equipment sales divided by total plant, property and equipment. Vertical lines denote NBER business cycle dates.

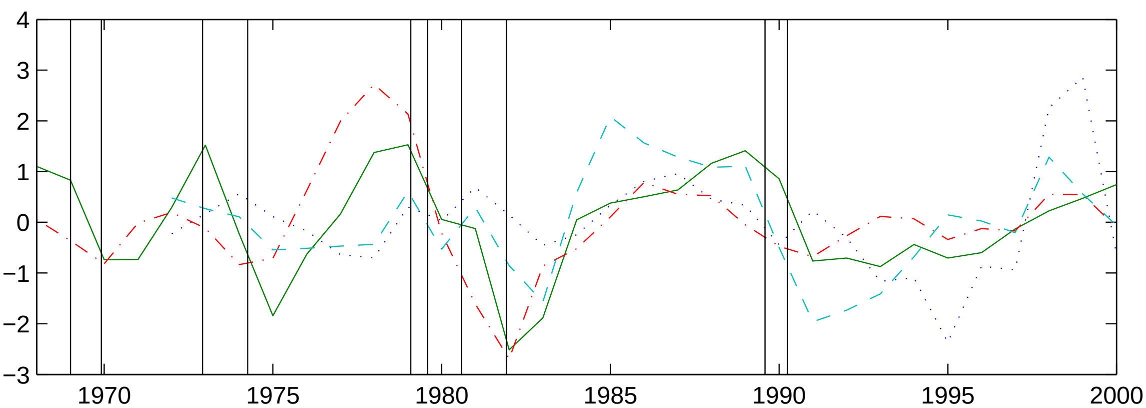

Figure 3: Labor Reallocation over the Cycle

Plotted series are the cyclical component of Hodrick-Prescott filtered data normalized by standard deviation. Solid line denotes log GDP, dotted line denotes gross job reallocation, and dashed line denotes excess job reallocation. Excess job reallocation is defined as gross job reallocation minus net changes in employment. Vertical lines denote NBER business cycle dates.

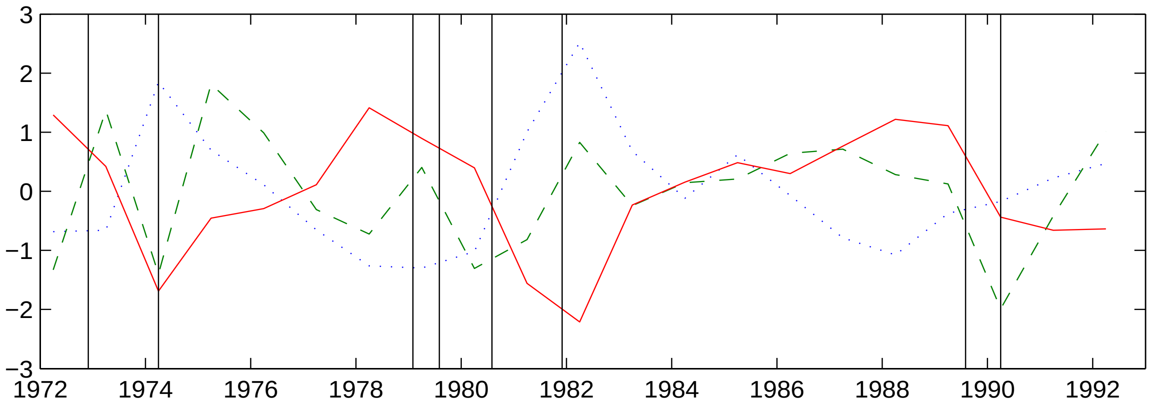

Figure 4: Dispersion in Total Factor Productivity Growth Rates over the Cycle

Plotted series are the cyclical component of Hodrick-Prescott filtered data. Solid line denotes log GDP, dashed line denotes standard deviation of total factor productivity growth rates across industries. Vertical lines denote NBER business cycle dates.

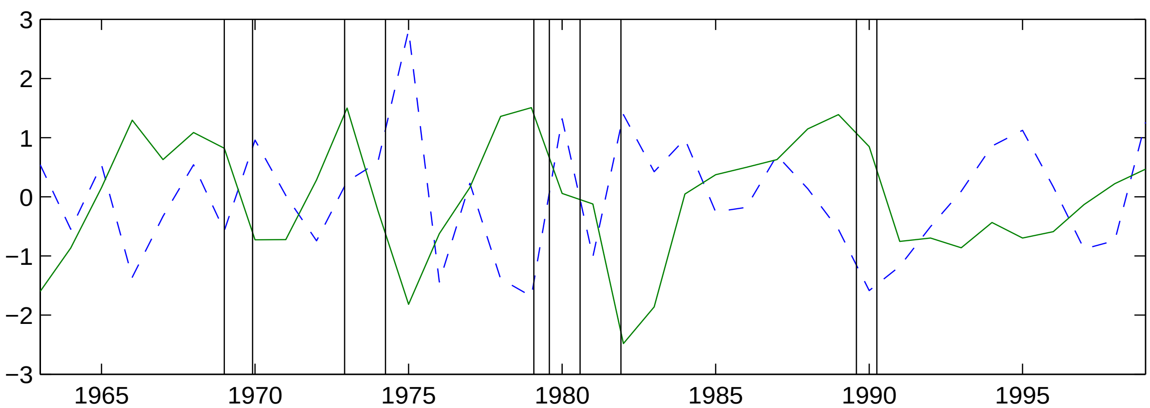

Figure 5: Dispersion in q over the Cycle

Plotted series are the cyclical component of Hodrick-Prescott filtered data. Solid line denotes log GDP, dotted line denotes standard deviation of q. The series plotted excludes values of q less than zero and greater than five. Vertical lines denote NBER business cycle dates.