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Capital Reallocation and Liquidity*

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First Draft: March 2002
This Draft: February 2003

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 flows of capital across firms and the benefits to capital reallocation using the cross sectional dispersion of Tobin's q, investment rates, total factor productivity, and capacity utilization. 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.

*We thank Steve Davis, Janice Eberly, John Fernald, Boyan Jovanovic, Arvind Krishnamurthy, Mitchell Petersen, Richard Rogerson, Matthew Shapiro, and seminar participants at the NBER Capital Markets in the Economy meeting, the SITE Liquidity and Distribution in Macroeconomics workshop, Northwestern University, the University of Michigan, the Federal Reserve Bank of Minneapolis, and the University of Chicago, and especially John Haltiwanger, our NBER discussant, for comments.

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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 reallocating capital are countercyclical. More capital flows between firms in booms even though differences across firms in terms of their abilities to put capital to its most productive use are larger in recessions. This seems puzzling. One would expect to observe more reallocation, not less, when opportunities for productive reallocation are abundant. These two empirical findings can be reconciled with a time varying cost of capital reallocation. We refer to this time varying reallocation cost as capital liquidity. Using a calibrated model with costly capital reallocation we find that the liquidity process which reconciles the empirical amount of capital reallocation with the associated benefits is procyclical, i.e., capital is more liquid in booms.

First, we document the business cycle properties of capital reallocation. We measure the amount of capital reallocation using data on sales of property, plant and equipment, acquisitions, and existing home sales. Since we want to study the reallocation of existing capital, we use measures which exclude net investment and retirements. We find that the amount of capital reallocation across firms is considerable and comprises about one quarter of total investment.[1] Sales of property, plant and equipment in turn constitute about one third of capital reallocation across firms. While there is a large literature on mergers, firms are actually more likely to reallocate capital by selling part of their property, plant and equipment. The median firm which is reallocating capital in any given year is doing so through such a sale. These transactions are smaller, but more frequent than mergers.

It is well known that investment is procyclical. However, less is known about the reallocation of existing capital.[2] We argue that existing capital is likely to be

[1]The amount of reallocation we find is consistent with that reported in Ramey and Shapiro (1998a) using a different measure. Ramey and Shapiro study changes in reallocation at the growth frequency and report that the aggregate amount of capital reallocation has increased over time.

[2]Notable exceptions are Ramey and Shapiro (1998a), Caballero and Hammour (1999, 2000), and Maksimovic and Phillips (2001).

illiquid because of informational or contractual specificities which tie capital to its current owner. These frictions may differ from those which affect new investment, precisely because the transaction involves existing assets. Moreover, reallocation and investment are driven by different shocks. Net investment is driven by aggregate productivity, while reallocation is driven by heterogeneity in firm level productivities. Hence the two series need not comove. We extract the cyclical component of each capital reallocation series and compute its correlation with the cyclical component of GDP. We find that capital reallocation is considerably and significantly procyclical.

Next we compare our findings on capital reallocation to those on labor reallocation, which has been widely studied in the literature. Although we do not model labor in this paper, one might expect capital reallocation and labor reallocation to have similar cyclical properties since labor and capital are complements in most standard production functions. Davis, Haltiwanger and Schuh (1996) show that gross job flows, measured as the sum of job creation and job destruction, are countercyclical. This stylized fact regarding the cyclical behavior of labor reallocation is not directly comparable to our results regarding capital reallocation since the gross job flows series includes net changes in employment. To construct a job flow series comparable to our capital reallocation series, one should exclude net flows into and out of unemployment since our measure of capital reallocation excludes net investment and retirements. We construct a series of excess job flows measured as gross job flows minus the absolute value of the net change in employment and find that excess job flows are weakly procyclical.[3] The excess job flows series better approximates a measure of flows of workers across firms and is therefore more comparable to our measure of capital reallocation across firms.

We are interested in using our findings for capital reallocation to infer the business cycle properties of the cost of reallocating capital, which we call capital liquidity. To impute the cyclical properties of the cost of reallocation, we need a measure of how much capital reallocation we would expect in booms compared to how much reallocation we would expect in recessions. In other words, we need a measure of

[3]Davis, Haltiwanger, and Schuh (1996) compare the amount of excess vs. gross job reallocation, but do not report the cyclical properties of excess job reallocation.

the benefits to reallocating capital over the cycle. We use measures of productivity dispersion across firms and industries to measure the benefits to reallocating capital. The idea is that we would expect more reallocation of capital when large productivity differences across firms create opportunities for productive reallocation. We illustrate this idea using our model of capital reallocation in Section 3.

We measure the benefits to reallocating capital using dispersion in investment opportunities, investment rates, total factor productivities, and capacity utilization. We find that dispersion in investment opportunities, measured by Tobin's q, is basically acyclical. Dispersion in investment rates, total factor productivity and capacity utilization are countercyclical. Thus, while the amount of reallocation is highly positively correlated with GDP at the business cycle frequency, the benefits to reallocation are not.

That measured dispersion is countercyclical suggests that the benefits to reallocation are higher in recessions than in booms. The fact that the benefits to reallocation are countercyclical while the amount of capital reallocation is procyclical can be reconciled by a cost of capital reallocation which is countercyclical. Our "identification" strategy relies on the fact that while contractual and informational frictions may be countercyclical, physical adjustment costs should not be. In fact, if physical adjustment costs are mainly opportunity costs measured in terms of lost output, then they will be procyclical. Thus we interpret the cyclical variation in the cost of capital reallocation as cyclical variation in contractual and informational frictions, which we refer to as "liquidity." Liquidity is hence procyclical.

We use our empirical findings as inputs into a calibrated model of capital reallocation in order to impute a measure of the variation in liquidity over the business cycle. Our model implements costly capital reallocation using a standard adjustment cost function. When capital is sold, the seller incurs a cost which is linearly homogenous in the amount of capital sold and the capital stock. We use this adjustment cost to proxy for capital illiquidity. We ask whether a model with calibrated aggregate and sector specific shocks can match the observed amount of reallocation and find the model is successful in this dimension. However, if dispersion in sector specific productivities are acyclical (a conservative calibration given that measured dispersion seems countercyclical in the data) then the model produces capital reallocation which is uncorrelated with output. To replicate the procyclical nature of capital reallocation found in the data we allow the cost of reallocating capital to vary countercyclically. This countercyclical cost leads to procyclical reallocation and does not alter other calibrated moments of the economy. The empirical findings combined with the output of the calibrated model imply that capital is less liquid in recessions than in booms. The cost of reallocation which comes closest to matching the correlation between output and reallocation in the data implies that the average cost in recessions is double the unconditional average.

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. However, this literature focuses on the effect of frictions on investment in new capital. In contrast this paper studies the reallocation of existing capital. Shleifer and Vishny (1992) and Eisfeldt (2002) do focus on secondary markets for capital but are not quantitative. In fact, little is known about the cyclical properties of capital liquidity. Most models of illiquidity employ contractual or informational frictions, and depend crucially on parameters which are very hard to measure empirically. In this paper, since the process for liquidity is imputed, we avoid the problem of measuring difficult objects like the amount of adverse selection or the level of agency costs.

Our model of capital reallocation builds on that in Ramey and Shapiro (1998b) who study capital reallocation due to sectoral shocks and show how industry shocks can reduce aggregate output when reallocation is costly.[4] We also build on recent work by Jovanovic and Rousseau (2002) who develop a theory of mergers as profitable reallocation due to dispersion in q and study merger waves. This paper is also related to studies of the effects of heterogeneity across firms on new investment, such as Hopenhayn (1992), Bertola and Caballero (1994), and Monge (2001), among others.

The paper proceeds as follows. Section 2 provides an empirical characterization of the business cycle properties of reallocation. We discuss the cyclical properties of

[4]For early models of the reallocation of labor due to sectoral shocks, see Lucas and Prescott (1974) and Rogerson (1987).

the reallocation of capital, the reallocation of labor, and the benefits to reallocation. Section 3 presents the model, discusses the calibration, and studies the implied business cycle properties of liquidity. Section 4 discusses possible explanations for the variation in the cost of reallocation with aggregate conditions. Section 5 concludes.

2 Business Cycle Properties of Reallocation

2.1 Capital Reallocation

In this section, we document the cyclical properties of capital reallocation. By capital reallocation we mean the reallocation of capital across firms, or households. We use three series to measure capital reallocation: sales of property, plant and equipment, acquisitions and existing home sales.[5] Ideally, we would like to use data on all reallocation of capital across firms and households, of which these three measures are only a subset. 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 use this turnover rate of capital to calibrate our model. We will focus on the reallocation of corporate assets in our model of capital reallocation, but have included the results for existing home sales to provide a broader characterization of the variation in reallocation and to show that the procyclical nature of reallocation is pervasive.

We define "reallocation" as the sum of acquisitions and sales of property, plant and equipment, and will calibrate our model to match the empirical properties of this series. Summing acquisitions and sales of property, plant and equipment is valid as long as only one side of every transaction is recorded in these series. Since capital expenditures are not broken down into expenditures on new and used capital, we think that this reallocation series is our best measure of the reallocation of existing capital which excludes new investment. Since there may be some sales of property, plant and equipment which are recorded as acquisitions by the purchaser, we also

[5]Our main data source is annual firm level data from Compustat. The data on existing home sales are from the National Association of Realtors. A detailed description of the data we use throughout the paper is in the appendix.

study each series individually.

Table 1 presents summary statistics for capital reallocation across firms. Reallocation constitutes 23.89% of investment, where investment is defined as capital expenditures plus acquisitions.[6] Depending on the measure of the capital stock, between 1.39% and 5.52% of the capital stock is reallocated on average each year. Out of total reallocation, property, plant and equipment sales account for 31.73%. Although we will not distinguish between acquisitions and sales of property, plant and equipment in the model, it is interesting to study the cyclical properties of each series separately. For example, one might expect that if capital illiquidity stems from organizational capital linked to the assets, then the sensitivity of reallocation to the cycle might depend on how bundled the transacted assets are.

Since we are interested in the cyclical properties of capital reallocation, it is important to detrend the reallocation and GDP series', since both are growing over the time period studied. We use the Hodrick-Prescott filter described in Hodrick and Prescott (1980) to extract the cyclical component of the log capital reallocation series' and of log GDP.[7] We deflate all series to 1996 dollars to remove any effects from variation in nominal prices. We compare the cyclical properties of the reallocation series to that of log GDP and also plot the series against NBER recession dates. Panel A of 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 and significant. For acquisitions the correlation is 0.675, for sales of property, plant and equipment it is 0.329, and for reallocation it is 0.637. For existing home sales the correlation is 0.614. 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

[6]Compustat measures capital expenditures as expenditures on property, plant and equipment excluding acquisitions.

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

components of the capital reallocation turnover series against GDP, and replicates the features of Figure 1.

Panel B of Table 2 describes how much more capital reallocation occurs in booms than in recessions by computing the ratio of the conditional mean of each reallocation series when GDP is above trend to that when GDP is below trend. Seventy one percent more acquisitions, thirty percent more sales of property, plant and equipment, and fifty nine percent more reallocation occurs when GDP is above trend than when GDP is below trend. Existing home sales are eleven percent higher when GDP is above trend.

Due to the fact that our data only includes sales of property, plant and equipment and does not include a separate measure of purchases of used capital, we measure only one side of these transactions. If the capital of firms which exit Compustat is reallocated and firms which exit do not gradually sell off their capital (which we would observe given our data) but rather are dropped from the sample, we may mismeasure the cyclical properties of reallocation. However, as long as exiting firms are as likely to be sold as going concerns as continuing firms are, the procyclical nature of acquisitions suggests that exits do not significantly change the properties of capital reallocation. Moreover Maksimovic and Phillips (1998) report that entry into bankruptcy, an event presumably related to exiting Compustat, by itself does not affect the probability that a firm sells assets. Finally, consistent with our findings, Maksimovic and Phillips (2001) report that in plant level census data the number of plants sold is higher in expansion years than in recession years.

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).[8] 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.

[8]Maksimovic and Phillips (2001) is an important exception.

2.2 Comparison to Labor Reallocation

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), hereafter DHS). This literature has documented 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. Using the DHS data we show that the correlation of the Hodrick-Prescott filtered job reallocation rate and the cyclical component of GDP is -0.890, significantly countercyclical. We also reaffirm the result which is the focus in DHS, namely the correlation with the cyclical component of the net change in employment, and find a correlation of -0.515 (see Table 3).

Since labor and capital are complements in most standard production functions, one might expect labor and capital reallocation to have more similar cyclical properties. However, it is important to notice that the capital reallocation and gross job flows series are not directly comparable, since the gross job flow series includes the net change in employment while our measure of capital reallocation excludes net investment and retirements by definition. To enable a comparison one should use a job flow series which excludes net flows into and out of unemployment. We construct a series of excess job flows measured as gross job flows minus the absolute value of the net change in employment, which is equivalent to taking (twice) the minimum of creation and destruction. The excess job flows series better approximates a measure of flows of workers across firms and is therefore more comparable to our measure of capital reallocation across firms. We find that excess job flows are very weakly procyclical and the correlation with detrended GDP is 0.011. Figure 3 plots the gross and excess job flows series. The correlation of excess job reallocation with the detrended net change in employment is 0.280. From this vantage point, a more consistent picture of the cyclical properties of reallocation of labor and capital emerges: the reallocation of labor across firms, like the reallocation of capital across firms, 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. Moreover, Caballero and Hammour (1999) argue that recessions reduce cumulative reallocation, which also might be more related to excess rather than gross reallocation. Finally, Boeri (1996) finds that gross job reallocation is either acyclical or mildly procyclical in other countries, and Foote (1998) finds that it is procyclical in most non-manufacturing sectors in the US.

How similar we should expect the cyclical properties of capital and labor reallocation to be depends on the degree of complementarity between capital and labor, the elasticity of labor supply, differences in the cost of reallocating labor vs. capital, etc., which we do not explore in this paper. However, it would be surprising if capital reallocation and labor reallocation were very negatively correlated. We compute the correlation of capital reallocation with both gross and excess job flows and find that the correlation with gross job flows is negative but the correlation with excess job flows is positive, consistent with our findings for GDP (see Table 3). There are, however, other differences between the DHS job flows series and our capital reallocation series. The DHS data measures job flows and not worker flows, whereas our measures track units of capital; the DHS data is for manufacturing firms only; and the DHS job flows are measured at the plant level.[9] Furthermore, capital is owned and thus in a sense deployed both before and after reallocation, whereas workers may transition through unemployment as the reallocation to a different job occurs. This explains the natural focus of the labor literature on gross flows rather than excess flows. However, we interpret the evidence overall as suggestive of a positive relation between capital and worker flows from one productive use to the next.

2.3 Benefits to Reallocation

Intuitively, capital reallocation should be driven by heterogeneity across firms in their ability to use capital productively. In section 3.1 we formalize this idea in the con-

[9]The dating of the labor reallocation data, discussed in the appendix, also suggests caution when interpreting these results.

text of our model. We show that, ceteris paribus, the amount of capital reallocation should be larger, the more dispersion there is in the marginal productivity of capital. We state the link between marginal productivities and q's, and marginal productivities and total factor productivities, and show that more dispersion in these variables should also coincide with larger amounts of capital reallocation. Accordingly, we call these dispersion measures measures of the "benefits" to capital reallocation, since they measure opportunities for productive reallocation. We study the cyclical properties of these and some alternative dispersion measures to assess how the benefits to capital reallocation vary over the business cycle.

In this paper, we do not take a stand on whether capital reallocation across industries or within industries across firms is more important. Our data on sales of property, plant and equipment only identifies one side of each transaction, so we do not know whether reallocation occurs within or across industries, what we know is that the capital is sold from one firm to another. We do know from the extensive literature on mergers that mergers both within and across industries are common. For robustness, we present dispersion measures at different levels of aggregation where possible. All measures paint a consistent picture. We document the cyclical properties of the following measures of the benefits to reallocation: the standard deviation of Tobin's q across firms, the standard deviation of investment rates across firms, the standard deviation of total factor productivity growth rates across industries, and the standard deviation of capacity utilization rates across industries.[10] In addition, we discuss measures of "reallocation shocks" studied in the labor literature, all of which are reported to be countercyclical. Consistent with these findings, all of our dispersion measures indicate that the benefits to capital reallocation are countercyclical, except for the dispersion in q's which is acyclical.

First, we study the cyclical properties of the benefits to reallocation using data on the dispersion in firm level q. According to standard q theory, capital should flow from firms with low q's to firms with high q's, and we reaffirm this in the context of

[10] All standard deviations are value weighted. Value weighting is motivated by the idea that dispersion across firms with larger capital stocks corresponds to larger amounts of capital reallocation. However, equal weighting yields very similar results for all measures.

our model below. The higher the dispersion in q, the more the economy can benefit from reallocation. In fact, our model (and many other standard models) implies that observing dispersion in q directly implies that there exists a friction in reallocating capital since otherwise q's should be equalized.

Panel A 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, i.e., we measure average q. We report three measures of the dispersion in q: the standard deviation of q's less than five, 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. Using an upper bound to exclude high q's likely subject to measurement error may bias the variation in the measured standard deviation and for this reason we also report dispersion using quartile differences.[11] The correlation of the cyclical components of dispersion in q and GDP varies quite a bit depending on the measure, from -0.130 to 0.134, however no correlation estimate is statistically significantly different from zero. The correlation between the cyclical component of dispersion in q's less than five and GDP is -0.130 and this series is plotted in Figure 4. We conclude that dispersion in q is essentially acyclical.[12]

Panel A also reports the correlation between the cyclical component of dispersion in firm level investment rates and GDP. Since investing at different rates is one way to reallocate capital, dispersion in investment rates is indicative of a motive for reallocation, assuming depreciation rates are similar. We find that the correlation between the dispersion of investment rates and GDP is negative, but not significant for the HP filtered series.

Next, 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

[11] Negative q's were always excluded. Abel and Eberly (2002) also use this selection criterion, excluding q's less than zero or greater than five.

[12] To compare to our industry level measures, we also computed dispersion in industry level q's, computed as industry level market value divided by industry level book value (at the two digit SIC code level) and found this dispersion to be acyclical as well.

TFP growth and thus we expect the benefits to reallocation to be high when the dispersion of TFP growth rates is high. Below, we show that in our model an increase in the difference between total factor productivities should increase the amount of reallocation which occurs. We use three measures of the cross-sectional dispersion of productivity growth rates (see Panel B of Table 4). The first measure computes the time series of the sectoral-output 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 -0.465. The second measure computes the time series of the sectoral value-added weighted standard deviation of total factor productivity growth rates (from the NBER-CES Manufacturing Industry database) across 458 durable and non-durable manufacturing industries at the four digit SIC code level.[13] The correlation between the cyclical component of sectoral TFP growth dispersion and the cyclical component of GDP is -0.384 using this measure.[14] The third 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.[15] The correlation between the cyclical component of sectoral dispersion in productivity changes and the cyclical component of GDP is -0.437. Thus, the dispersion of productivity according to these measures is countercyclical which suggests countercyclical benefits to reallocation. Figure 5 plots the cyclical component of the standard deviation of TFP growth rates across industries. The negative correlation is evident from the graph.

Another measure of the benefits to reallocation we propose is the dispersion of capacity utilization across sectors. A high dispersion of capacity utilization rates

[13]Schuh and Triest (1998) discuss a similar measure of dispersion using this data.

[14]We also computed within two digit SIC code industry dispersion in four digit SIC code industry level TFP growth. Within industry dispersion was countercyclical in sixteen out of twenty industries and the average correlation with GDP was -0.18.

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

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.

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. All studies report that these shocks are countercyclical. 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. To sum up, the various measures of cross-sectional dispersion studied in the literature are consistent with our findings of countercyclical dispersion.

3 Implied Business Cycle Properties of Liquidity

The data suggests the following facts about capital reallocation: capital reallocation is procyclical while the benefits to capital reallocation seem countercyclical. In this section we provide a calibrated model of costly capital reallocation consistent with these two facts and impute the business cycle properties of the liquidity of capital, i.e., the frictions involved in reallocating assets. The model suggests that these reallocation frictions have to be substantially countercyclical. We model the cost of reallocation as a standard adjustment cost incurred by the seller when capital is reallocated. However, we interpret the variation in the cost of reallocation as due to variation in informational and contractual frictions and hence variation in the liquidity of capital since it does not seem plausible that there is substantial countercyclical variation in the physical cost of reallocation. Thus, while our model uses adjustment costs to capture the cost of reallocation, we argue that the variation in this cost should be interpreted as variation in liquidity.[16]

3.1 Model

We develop a model where capital reallocation is an important feature of the economy in equilibrium. Reallocation of capital between firms or technologies is driven by idiosyncratic shocks to firm or technology 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.

We study the problem of maximizing the representative agent's utility by allocating the economy's capital amongst firms or technologies 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 C_t is the representative agent's consumption of the single consumption good, $u(C) = \frac{C^{1-\sigma}}{1-\sigma}$, $\beta < 1$, and $\sigma > 0$. Since our focus is on capital reallocation, we do not explicitly consider the labor-leisure choice and instead implicitly assume that labor is supplied inelastically.

[16] In support of the idea that capital liquidity varies and matters for reallocation decisions, Schlingemann, Stulz and Walkling (2002) find that for firms which stop reporting a segment, asset liquidity, measured by corporate transactions over assets within each two digit SIC code, is the most important determinant of whether that segment is sold vs. restructured within the firm.

The economy has two technologies which both produce the single consumption good. 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 moreover capital illiquidity may vary with the state of the economy. We model the cost of reallocation as an adjustment cost incurred by the seller.

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 (1998b). 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

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

where $A_{i,t}$ is the total factor productivity of technology i, $I_{i,t}$ is investment in technology i for next period, and F is the production function which we assume takes the following form: $F(\hat{K}_i) =, i = 1, 2$. Notice that we have assumed that both technologies produce the same consumption good and hence consumption has to be less than or equal to the sum of the output of the two technologies net of new investment. The law of motion for each type of capital, for all i and $i \neq j$, is

$$\hat{K}_{i,t} = K_{i,t} + R_{j\to i,t} - R_{i\to j,t} - \Gamma(R_{i\to j,t}, K_{i,t}) \tag{3}$$

$$K_{i,t+1} = (1-\delta)\hat{K}_{i,t} + I_{i,t}. \tag{4}$$

where Γ is the reallocation cost function which represents capital illiquidity, δ is the rate of depreciation with $1 > \delta > 0$, and $R_{i\to j,t} \geq 0$. Equation (3) describes the within period law of motion for capital in technology i: the capital deployed in technology i this period ($\hat{K}_{i,t}$) equals the amount of capital in technology i at the beginning of the period ($K_{i,t}$) plus the amount reallocated from technology j ($R_{j\rightarrow i,t}$) minus the amount reallocated to technology j ($R_{i\rightarrow j,t}$) minus the cost of reallocating capital to technology j ($\Gamma_R(R_{i\rightarrow j,t}, K_{i,t})$). Equation (4) implies that the capital in technology i at the beginning of period $t+1$ equals the amount of capital deployed in technology i in period t, i.e., the amount of capital in technology i after reallocation ($\hat{K}_{i,t}$), net of depreciation, plus the amount of new investment in period t. Capital illiquidity is modeled using the following reallocation cost function:

$$\Gamma(R_{i\rightarrow j,t}, K_{i,t}) \equiv \frac{\gamma}{2}\left(\frac{R_{i\rightarrow j,t}}{K_{i,t}}\right)^2 K_{i,t}, \tag{5}$$

with $\gamma \geq 0$. Thus, capital illiquidity is modeled by a quadratic cost function which is linearly homogenous in reallocation and the capital stock. The capital liquidity parameter γ determines how illiquid capital is. A higher γ implies that capital reallocation is more costly, or that capital is more illiquid. The reallocation cost captures illiquidity in the sense that when capital is more illiquid, sellers of capital incur a larger cost.

The functional form for the reallocation cost is the standard one used in models with adjustment costs on new investment (see Abel and Eberly (1994)). It captures the idea that reallocation is likely to be more costly when the fraction of capital which is reallocated is large. Note also that although there may be fixed costs due to capital illiquidity at the firm level (e.g., Table 1 shows that the median firm is not reallocating in any given year), firm level fixed costs do not imply fixed costs at the sectoral level.[17] Indeed, since in the aggregate data reallocation is never zero, we assume a cost function which implies that the marginal cost of reallocation is zero at zero reallocation such that the model predicts strictly positive reallocation at all times. For simplicity, we have assumed that new investment is frictionless.

Sectoral level productivities are given by the productivity processes $A_{1,t}$ and $A_{2,t}$ which are modeled as follows: The two technologies are assumed to be symmetric.

[17]See Cooper and Haltiwanger (2000) and Abel and Eberly (2002) for studies of the nature of capital adjustment costs implied by plant and firm level investment data respectively.

The logarithm of productivity of technology i is the sum of an aggregate productivity shock, z^a, and a technology specific productivity shock, z_i^s, that is,

$$\ln(A_{i,t}) = z_t^a + z_{i,t}^s. \tag{6}$$

We assume that $z_{i,t}^s = -z_{j,t}^s$, $i \neq j$, which means that the technology specific shocks are perfectly negatively correlated, and we can thus think of there being only one technology specific productivity shock which determines which technology is currently more productive. Furthermore, we assume that aggregate productivity and technology specific productivity are independent and both follow a Markov chain.

We will first consider an economy in which γ, the parameter in the reallocation cost function which determines capital liquidity, is constant. We then consider economies in which γ varies with the aggregate state of the economy, 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. Specifically, we will consider an economy in which $\gamma \equiv \gamma(z_t^a)$. This completes the description of the model.[18]

Reallocation is valuable in this model because at the beginning of each period, after the productivities of the two technologies have been revealed, capital can be reallocated to its most productive use. This can be seen using the first order conditions for the representative agent's problem which imply that:

$$(A_{i,t}\alpha\hat{K}_{i,t}^{\alpha-1}+(1-\delta))\times\left(1+\gamma\frac{R_{i\to j,t}}{K_{i,t}}\right) = (A_{j,t}\alpha\hat{K}_{j,t}^{\alpha-1}+(1-\delta))\times\left(1+\gamma\frac{R_{j\to i,t}}{K_{j,t}}\right). \tag{7}$$

Thus, the marginal product of capital times one plus the marginal cost of reallocation are equated across the two technologies. If reallocation is costless ($\gamma = 0$), then the marginal product of capital is equated across the two technologies and the economy

[18] We state the representative agent's problem for a stationary economy. This should be interpreted as the problem in a growing economy after adjusting for growth. Specifically, suppose that total factor productivity grows at $\exp(\rho)$ per period. Then all variables, $C_t, K_{i,t}, \hat{K}_{i,t}, R_{i\to j,t}, I_{i,t}$, grow at $\lambda \equiv \exp(\rho)^{1/(1-\alpha)}$. If the discount rate and depreciation rate in the growing economy are $\tilde{\beta}$ and $\tilde{\delta}$, respectively, then the stationary problem is obtained by rescaling all variables by λ^{-t} and setting $\beta \equiv \tilde{\beta}\lambda^{(1-\sigma)}$ and $1-\delta \equiv (1-\tilde{\delta})/\lambda$, except for a minor adjustment to the law of motion for capital which now reads $K_{i,t+1} = (1-\delta)\hat{K}_{i,t} + \lambda^{-1}I_{i,t}$. In the calibration and computation of the model we adjust for growth in this way.

reduces to a one technology economy. However, strictly positive reallocation costs introduce a wedge between the marginal products. Notice that whenever reallocation from technology i to j is positive, then reallocation in the opposite direction is zero. Hence, if capital is reallocated away from technology i, then the marginal product of capital in technology i is lower than the marginal product in technology j. The wedge is equal to the marginal cost of reallocation. Furthermore, if the economy begins the period with equal amounts of capital in both technologies, then an increase in the difference between the total factor productivity in the two technologies increases the amount of reallocation that occurs. This is the intuition which motivates measuring the "benefits to reallocation" by dispersion in total factor productivity as we did in Section 2.

We can also derive an expression for the marginal value of capital in each technology in our model, a version of marginal q. Using the envelope condition and the first order condition for the representative agent's dynamic program we have

$$\frac{\partial}{\partial K_i} v(z^a, z^s, K_1, K_2) = u'(C) \times \left(A_i \alpha \hat{K}_i^{\alpha-1} + (1-\delta)\right) \times \left(1 + \frac{\gamma}{2}\left(\frac{R_{i\to j}}{K_i}\right)^2\right). \quad (8)$$

Taking the consumption good as the numeraire, this means that the marginal value of each type of capital equals its marginal product times one plus the marginal reduction in reallocation cost. If reallocation is costless, then the marginal value equals the marginal product and the marginal value of both types of capital are equal since we showed above that the marginal products are equated in this case. Thus, if reallocation is costless there would be no dispersion in marginal q in this economy. When capital reallocation is costly however, there will be dispersion in marginal q across the two technologies. Whenever capital is reallocated away from a technology, then the marginal q of that technology is lower than the marginal q of the other technology. In addition, a higher dispersion in q implies higher dispersion in the marginal product of capital (assuming the last term in equation (8) is small) and hence more reallocation from equation (7). This is the rationale for using the dispersion of q as a measure of the benefits to reallocation.

3.2 Calibration

In this section we calibrate our model of capital reallocation. The parameterization is summarized in Table 5. The aim is to match the observed amount and cyclical properties of capital reallocation in a model which is consistent with the stylized facts about growth and business cycles.[19] We use standard parameter values wherever possible. In particular, we are interested in understanding to what extent reallocation costs need to vary countercyclically to explain the procyclical nature of reallocation. To be conservative, we calibrate the model assuming that sector specific technology shocks are acyclical rather than countercyclical as the data suggests.

Since our data is annual, the model is calibrated to annual data. We use standard values for preferences: the rate of time preference is assumed to be $\beta = 0.96$ and the coefficient of relative risk aversion is $\sigma = 2$. We set $\alpha = 0.333$ in the production function and set depreciation to $\delta = 0.1$. Both these values are common in the literature. The assumption about depreciation will imply an investment to capital ratio of 0.1. We assume that the growth rate λ is 0.0175.[20]

Aggregate productivity and technology specific productivity are each assumed to follow a two state Markov chain. The two Markov processes are assumed to be independent from each other. Specifically, we assume that aggregate productivity $z^a \in \{+\Delta^a, -\Delta^a\}$ and sector specific productivity $z_i^s \in \{+\Delta^s, -\Delta^s\}$. We assume that both productivity processes are described by a Markov transition matrix of the form

$$\Pi^a = \begin{bmatrix} \pi^a & 1-\pi^a \\ 1-\pi^a & \pi^a \end{bmatrix} \quad \text{and} \quad \Pi^s = \begin{bmatrix} \pi^s & 1-\pi^s \\ 1-\pi^s & \pi^s \end{bmatrix}. \tag{9}$$

To match the business cycle frequency, the transition probabilities are chosen such that the expected time until a switch in aggregate productivity occurs is 4 years, thus, $\pi^a = 0.75$. Similarly, we choose $\pi^s = 0.75$ which implies an expected time until a reversal of relative productivities of the two technologies of 4 years. Given these assumptions, the standard deviation of the aggregate productivity process is

[19]See Cooley and Prescott (1995).

[20]See footnote 18 for a discussion of where growth needs to be accounted for when computing the model. However, setting the growth rate equal to zero does not significantly alter the results.

$\sigma(z^a) = \Delta^a$ and the standard deviation of the technology specific shock is $\sigma(z^s) = \Delta^s$. We assume that $\Delta^a = 0.015$, implying an annual standard deviation of the logarithm of aggregate total factor productivity of 1.5%. Notice that the standard deviation of the growth rate, say g^s, of the sector specific shock is $\sigma(g^s) = \sqrt{1-\pi^s}2\Delta^s = \Delta^s$. The cross sectional standard deviation of productivity growth rates across industries in the data from Basu, Fernald, and Kimball (2001) is 5.7% and thus we choose $\Delta^s = 0.057$.

The parameters of the reallocation cost function are chosen to match the amount and cyclical properties of reallocation. Measures of the amount of reallocation in our data include the ratio of reallocation to investment, which is 23.89%, and the turnover rate of property, plant, and equipment, which is 1.75% (see Table 1, Panel B). In our model these correspond to the ratio of reallocation to new investment plus reallocation and the reallocation to capital ratio. We calibrate the model such that the ratio of reallocation to new investment plus reallocation equals 20%. This is a more conservative estimate of reallocation as a fraction of investment which adjusts for the possibility of double counting by assuming that half of property, plant and equipment sales are also recorded as acquisitions. To match this level of reallocation we set the capital liquidity parameter $\gamma = 0.05$.

Our measures of the cyclical properties of capital reallocation suggest a correlation of reallocation with output of between 0.329 and 0.675 (see Table 2). We will let the illiquidity of capital vary with aggregate productivity by assuming that γ is low (high) when aggregate productivity is high (low). Specifically, we assume that

$$\gamma(z^a) \in \{\gamma + \Delta^\gamma, \gamma - \Delta^\gamma\} \tag{10}$$

and follows a Markov processes which is perfectly negatively correlated with the process for aggregate productivity. Setting the liquidity variation parameter $\Delta^\gamma = 0$ recovers the case of constant illiquidity. We will study the cyclical properties of capital reallocation as we increase Δ^γ. We report results for $\Delta^\gamma = 0, 0.025$ and 0.05. Notice also that given this parameterization the unconditional expected illiquidity is held constant independent of Δ^γ.

3.3 Results

We have constructed a model and calibrated it to be consistent with the stylized facts about business cycles and growth. The goal is to impute the implied variation in the cost of reallocating capital, or capital liquidity, which generates a reallocation series consistent with the empirical moments described in Section 2. In Table 6 we report moments from three economies. The first economy features a constant reallocation cost chosen to match the empirical amount of reallocation. This economy produces moments consistent with the standard macroeconomic stylized facts, but fails to generate procyclical capital reallocation. The second and third economies allow capital illiquidity to vary with aggregate productivity by changing the liquidity variation parameter Δ^{γ}, with more variation allowed in the third. The third economy comes closest to generating the empirical correlation between capital reallocation and output using a reallocation cost which implies that the expected marginal cost of reallocating capital when productivity is low is about twice the unconditional expected marginal cost (Table 6 presents the model results.)[21]

The economy with constant capital illiquidity matches the empirical amount of capital reallocation by setting the capital liquidity parameter from equation (5) equal to 0.05. This implies that the reallocation cost must be small to match the empirical reallocation to investment and reallocation to capital ratios. The mean reallocation cost is small in our model because new investment is assumed to be costless. This allows costless reallocation of capital across technologies for the next period and thus reduces the benefit from instantaneous reallocation. By introducing an adjustment cost on new investment we could change the mean level of the reallocation cost predicted by the model. But since we are primarily interested in the cyclical properties of the illiquidity of existing capital we use the assumption of costless new investment to simplify the exposition and computation.[22] The expected marginal cost of reallocating an additional unit of capital is 0.0025 which represents 0.11% of

[21] Here, by "expected" we mean the cross sectional average given the stationary distribution of capital across sectors.

[22] We have computed a version of the model with adjustment costs on new investment, but this turns out not to significantly alter the results for the cyclical properties of reallocation.

average consumption. With this constant reallocation cost, and calibrated aggregate and sectoral specific shocks, reallocation is 20% of investment (where investment is defined as investment plus reallocation to be consistent with our empirical measure) and 2.5% of capital, in line with the empirical ratios in Table 1. This economy produces a capital output ratio of 2.3, an investment to capital ratio of 0.1, a standard deviation of log consumption of about one percent and a standard deviation of log output of about two percent, all in line with the standard macroeconomic stylized facts. However, this economy fails to match the procyclical nature of capital reallocation. The correlation between log reallocation and log output is basically zero both in levels and turnover rates, and the ratio of reallocation conditional on high vs. low productivity is about one. Notice that this is the case despite the fact that we have conservatively calibrated our dispersion shocks to be acyclical and that moreover the opportunity cost of reallocating capital in this model is indeed lower when aggregate productivity is low.

To generate procyclical capital reallocation, we modify the reallocation cost by varying the capital liquidity parameter with the aggregate state. We assume that it is more costly to reallocate capital, so that capital is less liquid, when productivity is low. We increase the liquidity variation parameter Δ^{γ} in equation (10) from zero to 0.025, and then to 0.05. The results for Δ^{γ}=0.025 are reported in Table 6. We focus here on the case where Δ^{γ}=0.05 since this case comes closest to generating the empirical correlation between capital reallocation and output. Importantly, changing the liquidity variation parameter does not alter the ability of the model to match the stylized facts for capital, output, investment and consumption. This economy produces a correlation between log reallocation and log output of 0.3848 and a ratio of reallocation conditional on high vs. low productivity of 1.5595. The correlation of 0.3848 is between the empirical correlations with GDP for sales of property, plant and equipment and acquisitions, and is lower than the 0.637 correlation for total reallocation, however the reallocation ratio is very close to the empirical ratio of 1.586. Given the low reallocation cost derived from the first economy in order to match the empirical level of liquidity, the third economy allows the maximum variation in liquidity; reallocation is free when productivity is high. The implied expected marginal cost of reallocating capital when productivity is low is about twice the unconditional expected marginal cost, and the implied average cost as a fraction of reallocation when productivity is low is about 2.6 times above the unconditional average cost.

We conclude that the combined business cycle properties for the amount of and benefits to reallocation imply substantial countercyclical variation in capital liquidity.

4 Discussion

Existing capital is likely to be illiquid because of informational or contractual specificities which tie capital to its current owner. The approach we have chosen here is to model the illiquidity or cost of reallocation directly as an adjustment cost and to argue that this cost needs to be countercyclical to be consistent with the data. There does not seem to be a reason to believe that the physical costs of reallocating capital are countercyclical themselves. In addition, the opportunity costs of reallocation in terms of forgone production are presumably procyclical. Thus, we interpret the variation in reallocation frictions implied by our model as variation in the endogenous frictions such as informational or contracting frictions. But why are these frictions in the market for used capital countercyclical?

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. Thus, the effect of credit constraints on the amount of capital reallocation is ambiguous in general. In fact, models which predict fire sales or forced selling by liquidity constrained firms in bad times would predict more reallocation in recessions not less. To be consistent with the procyclical nature of capital reallocation in the data, the credit constraints of potential buyers should vary more with aggregate conditions than those of sellers. Or, to the extent that the market for used capital is intermediated, countercyclical credit constraints of such intermediaries might explain countercyclical illiquidity.

The amount of adverse selection in the market for used capital might also 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 assets and the fundamental amount of asymmetric information do not vary with productivity. This is due to the fact that when productivity is low, there are fewer "non-informational" reasons for trade and hence the secondary market is more subject to adverse selection in bad times.

In our opinion, the countercyclical credit constraints and countercyclical adverse selection interpretations of the variation in capital liquidity are 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, and this is not the case in our data. In fact, the median investment to lagged property, plant and equipment ratio for firms which sell PP&E is 21% compared to 23% 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, however, play a more important role in explaining procyclical housing sales.

Second, 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 study how large this effect might be using a calibrated model.

5 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 capital liquidity appears procyclical.

Appendix: Data Sources

Macroeconomic Data: Annual and quarterly GDP data is from the FRED database at the Federal Reserve Bank in St. Louis (http://research.stlouisfed.org/fred). We use data from 1963 to 2000. Annual CPI data for all urban consumers is from the Bureau of Labor Statistics (http://www.bls.gov). NBER business cycle dates are from the National Bureau of Economic Research (http://www.nber.org/). We use the monthly dates in the figures.

Assets, Property, Plant and Equipment, Capital Expenditures, Acquisitions and Property, Plant and Equipment Sales Data: Data on assets, property, plant and equipment, and capital expenditures are reported in Compustat annual data items 6, 8 and 30, respectively. Acquisitions and sales of property, plant 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 property, plant and equipment was created analogously as follows: Firm year observations in which the property, plant and equipment entry contained a combined data code were excluded. For the property, plant and equipment turnover rate, total property, plant and equipment was summed over firms by year using the same inclusion rule.

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.

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.

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. Obvious cases of measurement error led us to introduce an upper bound for economically reasonable q's. The standard deviations of q's less than 5 are standard deviations of q's weighted by market value for all q's less than 5. We also computed weighted quartiles of q for all positive q's as an additional check on the effect of this upper bound.

Total Factor Productivity Data at the Two Digit SIC Code Level: 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 the productivity growth (log differences) across sectors is computed by weighting the industries by the value of sectoral output at the end of the year.

Total Factor Productivity Data at the Four Digit SIC Code Level: The annual data on total factor productivity and industry value added is from the NBER-CES Manufacturing Industry Database (http://www.nber.org/). We use data for 458 durable and non-durable manufacturing industries at the four digit SIC code level from 1963 to 1996 covering all manufacturing industries at the two digit level (SIC 20-39). SIC code 3292 is excluded due to missing data. The standard deviation of productivity growth across sectors is computed by weighting the industries by the total value added 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.

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Table 1: Summary Statistics for Compustat Capital Reallocation Data

Level variables are in millions of 1996 dollars. 'PP&E' stands for property, plant and equipment and 'CapEx' for capital expenditures. 'Reallocation' is used to abbreviate the sum of acquisitions plus sales of PP&E. Reallocation ratios in Panel B are computed as the ratio of the sample mean of the numerator to the sample mean of the denominator. Investment is defined as the sum of capital expenditures plus acquisitions.

Panel A: Summary Statistics

Variable	Mean	Median	Std. Dev.
Assets	2149.75	91.74	14691.73
PP&E	525.11	16.43	3094.69
CapEx	101.12	3.45	660.13
Acquisitions	19.71	0	236.63
Sales of PP&E	9.16	0	79.63

Panel B: Reallocation Ratios

Flow Ratios	
Reallocation/Investment	23.89%
Reallocation/CapEx	28.55%
Acquisitions/CapEx	19.49%
Sales of PP&E/CapEx	9.06%
Sales of PP&E/Reallocation	31.73%
Turnover Rates	
Acquisitions/Assets$_{(t-1)}$	0.95%
Sales of PP&E/PP&E$_{(t-1)}$	1.75%
Reallocation/Assets$_{(t-1)}$	1.39%
Reallocation/PP&E$_{(t-1)}$	5.52%

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: Acquisitions are divided by lagged total assets, Property, Plant and Equipment Sales by lagged total property, plant and equipment and Existing Home Sales are divided by a measure of the total housing units. Acquisitions and Sales of Property, Plant and Equipment are deflated by the CPI. Reallocation is defined as the sum of acquisitions and sales of property, plant and 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 conditional mean of reallocation over years where GDP is above trend to the conditional mean 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
Acquisitions	0.675	0.437	0.566	0.404
	(0.122)	(0.236)	(0.133)	(0.207)
Sales of Property, Plant and Equipment	0.329	0.431	0.220	0.377
	(0.173)	(0.184)	(0.161)	(0.197)
Reallocation	0.637	0.511	0.540	0.414
	(0.112)	(0.193)	(0.139)	(0.206)
Existing Home Sales	0.614	0.489	0.605	0.507
	(0.204)	(0.271)	(0.195)	(0.240)

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

Variable	High/Low Output Reallocation Ratio			
	HP Level	LT Level	HP Turnover	LT Turnover
Acquisitions	1.707	1.195	1.598	1.215
Sales of Property, Plant and Equipment	1.326	1.091	1.165	1.086
Reallocation	1.586	1.164	1.281	1.125
Existing Home Sales	1.109	1.033	1.132	1.137

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. Reallocation is the sum of acquisitions plus sales of property, plant and 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.

	Correlation of Output with		Correlation of Net Change in Employment with		Correlation of Reallocation with	
Variable	HP	LT	HP	Not Detrended	HP	LT
Job Reallocation	-0.890	-0.831	-0.515	-0.398	-0.455	-0.121
Rate	(0.082)	(0.144)	(0.290)	(0.320)	(0.223)	(0.252)
Excess Job Re-	0.011	0.021	0.280	0.258	0.094	0.147
allocation Rate	(0.327)	(0.355)	(0.348)	(0.408)	(0.354)	(0.353)

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 (market value-weighted) standard deviation of Tobin's q across firms is computed using market to book ratios computed using data from Compustat. The time series of the (lagged property, plant and equipment weighted) standard deviation of investment rates is computed using firm level ratios of capital expenditures to lagged property, plant and equipment. The time series of the (output-weighted) standard deviation of total factor productivity growth rates and capacity utilization across industries at the two digit SIC code level 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. The time series of the (value-added weighted) standard deviation of total factor productivity growth rates across industries at the four digit SIC code level is computed using data from the NBER-CES Manufacturing Industry database on durable and non-durable manufacturing industries. 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. 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. See the Appendix for details.

Panel A: Dispersion in Tobin's q and in Investment Rates

	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	0.134	0.137
	(0.122)	(0.181)
Difference between 3rd and 1st Quartile	0.110	-0.017
Divided by the Median of Tobin's q	(0.266)	(0.296)
Standard Deviation of Investment Rates	-0.145	-0.472
	(0.230)	(0.258)

Panel B: Dispersion in Total Factor Productivity and in Capacity Utilization

	Correlation of Output with	
Variable	HP	LT
Standard Deviation of TFP Growth Rates	-0.465	-0.122
(Two Digit SIC Code Level)	(0.194)	(0.258)
Standard Deviation of TFP Growth Rates	-0.384	-0.228
(Four Digit SIC Code Level)	(0.174)	(0.229)
Standard Deviation of Productivity Changes	-0.437	-0.244
Adjusted for Capacity Utilization	(0.264)	(0.338)
Standard Deviation of Capacity Utilization	-0.672	-0.560
	(0.204)	(0.261)

Table 5: Parameter Values for Calibration

Preferences						
β	σ					
0.96	2					
Technology						
α	δ	λ	π^a	π^s	Δ^a	Δ^s
0.333	0.1	0.0175	0.75	0.75	0.015	0.057
Capital Liquidity Parameters						
γ	Δ^γ					
0.05	{0,0.025,0.05}					
Discretized State Space						
K_i	$R_{i\to j}$					
[3.15 : 0.03 : 3.93]	[0 : 0.01 : 0.55]					

Table 6: Simulation Results

Panel A: Capital, Output, Investment, and Consumption

	Liquidity Variation Parameter (Δ^γ)		
Variable	0	0.025	0.05
Ratios			
$E[K]/E[Y]$	2.3108	2.3113	2.3118
$E[I]/E[K]$	0.1000	0.1000	0.1000
Standard Deviations			
$\sigma(\ln(Y))$	0.0178	0.0178	0.0178
$\sigma(\ln(I))$	0.0537	0.0533	0.0535
$\sigma(\ln(C))$	0.0106	0.0107	0.0107

Panel B: Reallocation

	Liquidity Variation Parameter (Δ^γ)		
Variable	0	0.025	0.05
Ratios			
$E[R]/(E[I]+E[R])$	0.1977	0.1984	0.2057
$E[R]/E[K]$	0.0246	0.0248	0.0259
Correlations			
$\rho(\ln(R),\ln(Y))$	0.0062	0.1969	0.3848
$\rho(R/K,\ln(Y))$	-0.0069	0.1467	0.2942
Conditional Moments			
$E[R\vert z^a=+\Delta^a]/E[R\vert z^a=-\Delta^a]$	1.0095	1.2529	1.5595
Reallocation Costs			
Average Costs ($E[\Gamma]/E[R]$)	0.0017	0.0015	0.0011
Average Costs when $z^a=-\Delta^a$ (Relative to Mean)	0.997	1.483	2.559
Marginal Costs ($E[\frac{\partial}{\partial R}\Gamma]$)	0.0025	0.0023	0.0022
Marginal Costs when $z^a=-\Delta^a$ (Relative to Mean)	1.000	1.415	2.000

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, dashed line denotes acquisitions, dotted line denotes property, plant and equipment sales, and dash-dotted line denotes existing home sales. Vertical lines denote NBER business cycle dates.

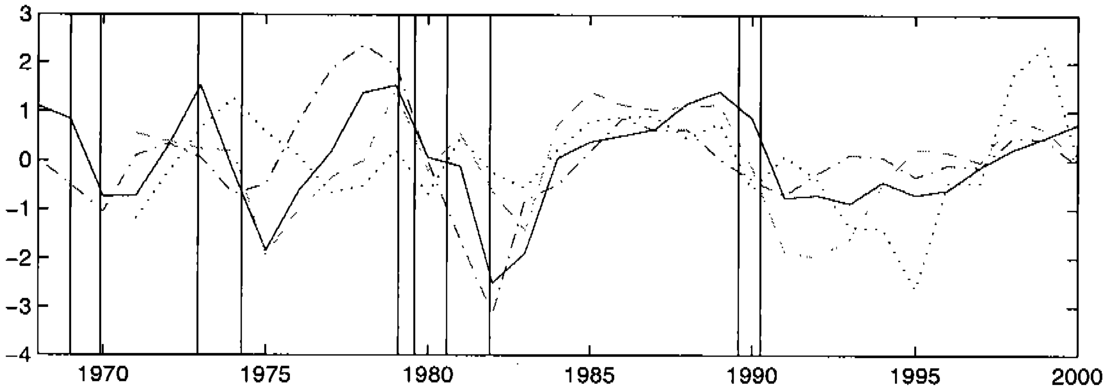

Figure 2: Turnover Rates of Capital over the Cycle

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

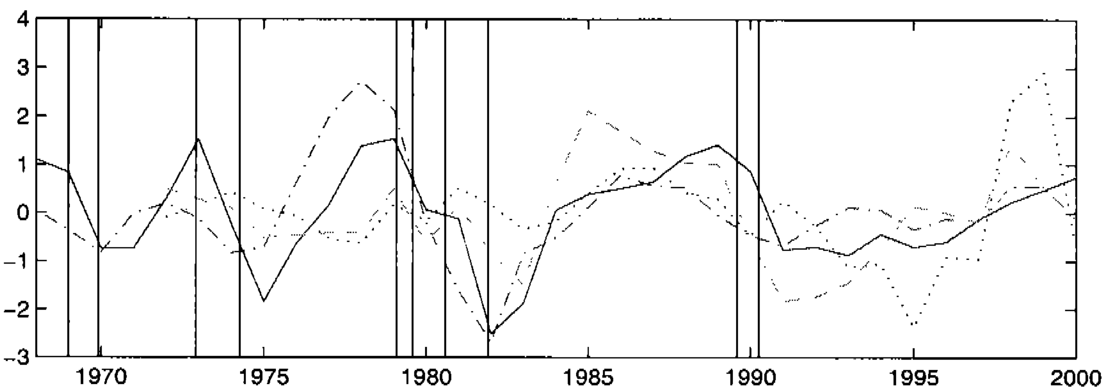

Figure 3: Labor Reallocation over the Cycle

Plotted series are the cyclical component of Hodrick-Prescott filtered data normalized by standard deviation. Solid line denotes 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.

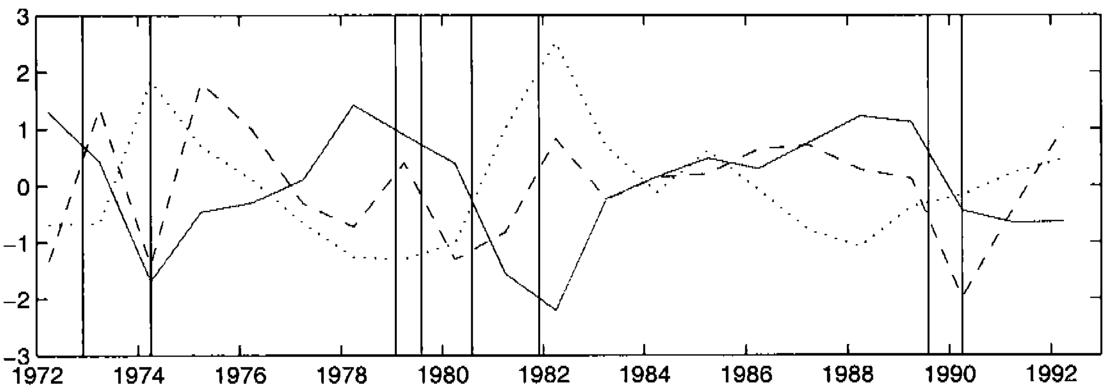

Figure 4: Dispersion in q over the Cycle

Plotted series are the cyclical component of Hodrick-Prescott filtered data. Solid line denotes GDP and 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.

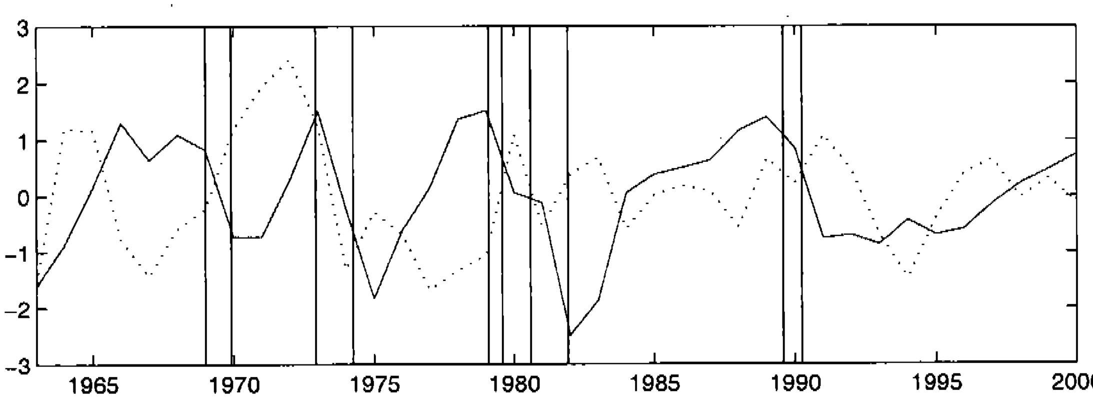

Figure 5: Dispersion in Total Factor Productivity Growth Rates over the Cycle

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