

Capital reallocation and liquidity*

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Abstract

This paper shows that the amount of capital reallocation between firms 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 several measures of the cross sectional dispersion of the productivity of capital. We then study a calibrated model economy where capital reallocation is costly and impute the cost of reallocation. We find that the cost of reallocation needs to be substantially countercyclical to be consistent with the observed joint cyclical properties of reallocation and productivity dispersion.

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1 Introduction

How does capital reallocation and capital liquidity vary over the business cycle? Our paper addresses this question by first documenting the business cycle properties of capital reallocation and then using the cyclical properties of capital reallocation to infer the business cycle properties of the frictions involved in reallocating capital, i.e., capital liquidity.

In short, we will establish the following two facts: First, capital reallocation, i.e., the reallocation of productive assets across firms, is procyclical. Second, the cross sectional standard deviation of capital productivity is countercyclical by several measures. It is the joint observation of these two facts which is interesting. We argue that the cross sectional dispersion of the ability to put capital to its most productive use measures the benefits to capital reallocation. Thus, capital reallocation is procyclical even though the measured benefits appear countercyclical. Together, these two empirical findings suggest that the costs or frictions involved in reallocating capital are countercyclical. We interpret this time varying reallocation cost as capital liquidity, broadly defined. We use the term liquidity to encompass the informational and contractual frictions which inhibit capital reallocation, such as adverse selection, agency problems, and financing constraints, since any physical costs are unlikely to vary and, if anything, might be expected to vary procyclically. Using a calibrated model with costly capital reallocation we find that the liquidity process which reconciles the empirical amount of and benefits to capital reallocation needs to be substantially countercyclical. Using our calibration the implied cost of reallocating capital is 2.6 times higher in recessions than on average.

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, and acquisitions. Thus, we study transfers of ownership which do not necessarily involve the physical movement of capital. In our model, the productivity of capital is determined by the technology in which it is deployed. When capital is reallocated the new productivity applies. Our empirical measure of reallocation captures instances when existing capital is sold or acquired. We implicitly assume that the productivity of a unit of capital is not embedded in the capital itself, but

is determined by who deploys it. Thus, a firm defines a “technology.” If capital is reallocated to a new firm, the new productivity applies. Accordingly, our measure captures transactions after which capital is deployed by a new firm.

Our measure of capital reallocation suits our purposes for three reasons: First, since we want to study the reallocation of existing capital, we need a measure which excludes new investment and scrapping. Second, our measure of reallocation is supported by the micro evidence which suggests that changes in ownership affect productivity, that capital typically flows from less productive to more productive firms, and that the productivity of acquired capital increases.¹ Finally, our measure of reallocation is consistent with our use of the term liquidity to denote the informational and contractual frictions which inhibit potential buyers and sellers of real assets from realizing the gains from capital redeployment.

For our measure of capital reallocation, we extract the cyclical component and compute the correlation with the cyclical component of GDP. We find that capital reallocation is considerably and significantly procyclical. The correlation between the cyclical components of reallocation and GDP is 0.64. Moreover, we find that the amount of capital reallocation across firms is considerable, comprising about one quarter of total investment.

We want to use the cyclical properties of capital reallocation to learn about the cyclical properties of capital liquidity. To do this, we need a measure of how much capital reallocation we would expect over the cycle, i.e., we need a measure of the benefits to capital reallocation. We use several measures of productivity dispersion to measure the benefits to reallocating capital, including dispersion in firm level Tobin’s q , dispersion in firm level investment rates, dispersion in total factor productivity growth rates, and dispersion in capacity utilization. The idea is that we would expect more reallocation of capital when large productivity differences create opportunities for productive reallocation. Our dispersion measures attempt to capture at the macro

¹For the relationship between capital transactions and capital productivity, see Maksimovic and Phillips (2001) and Schoar (2002) for evidence using TFP measures, Jovanovic and Rousseau (2002) for evidence using Tobin’s q , and Lang, Stulz, and Walkling (1989), Servaes (1991), Lang, Poulsen, and Stulz (1995), and Andrade, Mitchell, and Stafford (2001), for evidence using measures of Tobin’s q and post-transaction financial performance.

level the benefits to reallocation which have been argued to explain reallocation at the micro level. We illustrate this idea using our model of capital reallocation in section 3.

For each dispersion measure, we extract the cyclical component and compute the correlation with the cyclical component of GDP. Dispersion in investment rates, total factor productivity growth rates, and capacity utilization is countercyclical, and dispersion in investment opportunities, measured by Tobin's q , is basically acyclical. Thus, while the amount of reallocation is highly positively correlated with GDP at the business cycle frequency, the benefits to reallocation are not.

The fact that dispersion in the productivity of capital is countercyclical is interesting in its own right. Our dispersion measures describe the degree of heterogeneity in productivity across firms and sectors over the business cycle. Recently, evidence for countercyclical heterogeneity has been found in labor income, consumption, and stock returns as well, and has been theoretically linked to endogenous informational and contractual frictions.² Our finding of countercyclical productivity dispersion across firms and sectors adds to the empirical support for increases in heterogeneity in recessions.

We use these two empirical findings as inputs into a calibrated model of capital reallocation in order to impute a quantitative measure of the variation in reallocation frictions or liquidity over the business cycle. We model capital illiquidity using a standard adjustment cost function. The benefit of this modeling strategy is that we can generate a quantitative estimate of the variation in capital liquidity over the cycle. The cost of our modeling strategy is that the functional form for capital illiquidity is exogenously specified. We motivate our modeling choice for capital illiquidity in detail in section 3.1.

We construct a model with aggregate and sector specific shocks and calibrate the model to match the standard macroeconomic stylized facts for the capital output ratio, investment to capital ratio, the standard deviation for aggregate productivity

²See Storesletten, Telmer, and Yaron (2004) for evidence of countercyclical dispersion in labor income and consumption, Rampini (2004) for a model which generates countercyclical dispersion in income and consumption due to countercyclical agency costs, and Campbell, Lettau, Malkiel, and Xu (2001) for evidence of countercyclical dispersion in stock returns.

growth, and the standard deviation of log consumption. The standard deviation of technology specific productivities is calibrated to match that in sectoral level data since we study a simple, two technology model. The unconditional average reallocation cost is then calibrated to match the empirical capital turnover rate. We find that if the dispersion in technology specific productivities is acyclical (a conservative calibration given that measured dispersion appears countercyclical in the data) and capital liquidity does not vary, then the model produces capital reallocation which is essentially uncorrelated with output. To replicate the empirical procyclical nature of capital reallocation we allow the cost of reallocating capital to vary countercyclically. We find that countercyclical capital illiquidity leads to procyclical reallocation and does not alter the other calibrated moments of the economy. To match the observed ratio of capital reallocation when GDP is above trend to that when GDP is below trend of 1.6, the implied cost of reallocating capital must be 2.6 times higher in recessions than on average.

Our interpretation of our empirical findings combined with the output of the calibrated model is that capital is less liquid in recessions, i.e., that there are more informational and contractual frictions associated with reallocating capital in recessions than in booms. 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. In this sense, our findings are related to the investigation of the nature of capital adjustment costs and suggest that non-physical costs are important for the type of reallocation we consider.³ We discuss possible micro foundations for capital illiquidity along with some alternative explanations of the joint observation about capital reallocation and dispersion in section 4.

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 (2004), for example, generate countercyclical agency costs. However, this literature focuses on the effect of frictions on investment in new capital. In contrast this

³See Cooper and Haltiwanger (2000) and the references therein.

paper studies the reallocation of existing capital. Shleifer and Vishny (1992) and Eisfeldt (2004) do focus on secondary markets for capital but are not quantitative. In fact, little is known about the cyclical properties of capital liquidity empirically. Most models of illiquidity employ contractual or informational frictions and depend crucially on parameters which are very hard to measure. By imputing the process for liquidity, we avoid the problem of measuring difficult quantities like the amount of adverse selection or the level of agency costs directly.

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 Our work is also related to Jovanovic and Rousseau (2002) who develop a theory of merger waves as profitable reallocation due to dispersion in q .⁵

Finally, 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. We replicate this result and show that gross job flows are negatively correlated with our capital reallocation series. However, excess job reallocation, which excludes net changes in employment and is therefore more comparable to our reallocation measure, is weakly procyclical and weakly positively correlated with capital reallocation.⁶ Note that the results of our comparison are only suggestive since there are other substantive differences between the job and capital reallocation measures, which we discuss in section 4. In particular, the two measures differ since we measure the reallocation of capital across controlling owners whereas the labor literature measures physical reallocation of jobs across plants.

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

⁵There is a large literature on mergers. However, the focus of that literature is on merger waves and hence the frequency studied is lower than that of the business cycle.

⁶Davis, 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 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 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 and compares our findings for capital reallocation to the findings in the literature on labor reallocation. 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 existing productive assets across firms. We measure the amount of capital reallocation using annual data on sales of property, plant and equipment, and acquisitions.⁷ Thus, we capture transactions after which the traded capital is redeployed by a new firm. We define “reallocation” to be the sum of acquisitions and sales of property, plant and equipment, and focus on the cyclical properties of this series and its turnover rate.

Our reallocation measure thus captures instances when existing capital is sold or acquired.⁸ Since we measure the benefits to reallocation using measures of dispersion in capital productivity, we assume that the firm where a unit of capital is deployed determines the productivity of that capital. If capital is reallocated to a new firm, the new productivity applies. Under this assumption our measure of the amount of capital reallocation is consistent with our measure of the benefits to capital reallocation. This measure of reallocation is supported by the existing micro evidence. Maksimovic and Phillips (2001) find that asset sellers have below average productivity while buyers tend to have higher than average productivity, that transferred assets increase in productivity, and that the average productivity of buyers and

⁷Our main data source is annual firm level data from Compustat. A detailed description of the data we use throughout the paper is in the appendix.

⁸See Jovanovic and Rousseau (2002) for a similar definition of capital reallocation.

sellers' existing assets is an important determinant of post trade productivity gains. Likewise, Schoar (2002) finds that the productivity of acquired plants is declining and lower than average prior to being reallocated, and that after reallocation productivity increases.

It is well known that investment is procyclical. However, less is known about the reallocation of existing capital.⁹ We argue that existing capital is likely to be 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 transactions involve existing assets. For example, collateralized borrowing might be easier for existing assets than for new investment, but the current owner of an existing asset may be more likely to have private information about asset quality or to receive non-contractible private benefits from owning the asset. Moreover, reallocation and investment are driven by different shocks. New investment is driven by aggregate productivity, while reallocation is driven by heterogeneity across firm level productivities. Hence, the two series need not comove.

Overall, the amount of reallocation is considerable. Table 1 presents summary statistics for capital reallocation across firms. Reallocation of existing capital comprises about one quarter of total investment, where investment is defined as capital expenditures plus acquisitions.¹⁰ Depending on the measure of the capital stock, between 1.4 percent and 5.5 percent of the capital stock turns over each year.¹¹ 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 and acquisitions,¹²

⁹Notable exceptions are Ramey and Shapiro (1998a), who document the properties of capital reallocation at the growth frequency and study whether reallocation shocks lead to lower aggregate output, Caballero and Hammour (2001, 2005), and Maksimovic and Phillips (2001).

¹⁰Compustat measures capital expenditures as expenditures on property, plant and equipment excluding acquisitions.

¹¹The turnover rate for 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. It is also consistent with the reallocation rates of plants in the census data reported in Maksimovic and Phillips (2001).

¹²See Andrade, Mitchell, and Stafford (2001) and Holmström and Kaplan (2001) for recent surveys.

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 acquisitions. Although we will not distinguish between acquisitions and sales of property, plant and equipment in our model, and instead focus on the fact that both series represent capital reallocation, it is interesting to study the cyclical properties of each series separately. For example, one might expect that if capital illiquidity stems from organization capital linked to the assets, then the sensitivity of reallocation to the cycle might depend on how bundled the traded assets are. Likewise, specific investments probably do not scale linearly in the size of the asset, but are instead likely to be larger in percentage terms for divisions as opposed to pieces of equipment.

Since we are interested in the cyclical properties of capital reallocation, it is important to detrend the reallocation and GDP series', since the raw series are non-stationary. We use the Hodrick-Prescott filter described in Hodrick and Prescott (1997) to extract the cyclical component of the log capital reallocation series' and of log GDP.¹³ We deflate all series to 1996 dollars using the CPI from the BLS to remove any effects from variation in nominal prices. We also study turnover rates, or reallocation normalized by the subset of the capital stock included in our data to account for the fact that Compustat only includes a subset of all firms. Our model is calibrated to match the level of this turnover rate and the cyclical properties of the reallocation series.

We document the cyclical properties of capital reallocation in Table 2 and illustrate the procyclical nature of capital reallocation in Figures 1 and 2. The correlation of output and capital reallocation is presented in Panel A of Table 2. 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, with a point estimate of 0.637. For acquisitions the correlation is 0.675, and for sales of property, plant and equipment it is 0.329. Standard

¹³To extract the cyclical component from annual data we use a weight of 100 in the filter. Results at the quarterly frequency are qualitatively similar. However, the quarterly Compustat data is only available since 1984.

errors corrected for heteroscedasticity and autocorrelation are reported in the table. Moreover, the procyclical nature of capital reallocation can be seen clearly when graphed. All reallocation series move together and comove with GDP. Figure 1 plots the cyclical components of the capital reallocation series against that of GDP. Note that NBER recession dates, also plotted, 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 Figure 1.

Panel B of Table 2 further 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. Fifty nine percent more reallocation occurs when GDP is above trend than when GDP is below trend. Seventy one percent more acquisitions and thirty percent more sales of property, plant and equipment occur in booms relative to recessions. We will impute the process for capital liquidity which generates the ratio of capital reallocation in booms vs. recessions of 1.6 using our calibrated model in section 3.1.

Studying the capital turnover rates alleviates the effects of any variation in capital prices which remains after deflating by the CPI. However, we also studied the cyclical properties of reallocation using alternative capital price deflators and found essentially the same results. The correlation between the cyclical component of GDP and reallocation deflated by the NIPA non-residential private fixed investment price index is 0.633. Using the price index of the average machine constructed by Cummins and Violante (2002) this correlation is 0.578.¹⁴ Moreover, the correlation between the cyclical component of GDP and the turnover rate of capital defined as reallocation normalized by the total market value of Compustat firms in each year is 0.548. Thus, our findings do not seem to be driven by variation in capital prices.¹⁵

As noted in the introduction, our reallocation series suits our study because it

¹⁴We thank Jason Cummins and Giovanni Violante for providing us with their price index data.

¹⁵Interestingly, Greenwood, Hercowitz, and Krusell (1997, 2000) report that the correlation between the cyclical component of the relative price of new equipment and both new investment and aggregate output is actually negative. However, using their price index as a deflator, we again find essentially the same correlation between the cyclical component of GDP and reallocation, namely 0.639.

excludes new investment, measures transactions which have been shown in the micro literature to affect capital productivity, and is consistent with our use of the term liquidity to denote frictions which inhibit buyers and sellers of capital from consummating transactions. Since capital expenditures are not decomposed 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.¹⁶ One concern might be that 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, and that we hence mis-measure 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 alter the cyclical 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.

Although our focus is on the reallocation of corporate assets, we 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.¹⁷ For existing home sales the correlation between the cyclical component of sales and GDP is 0.614, and existing home sales are eleven percent higher when GDP is above trend. Interestingly, the focus of most of the finance and real estate economics literature is 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).¹⁸ The finding in both the finance and real estate literature is that

¹⁶We have constructed a capital “creation” and “destruction” series using Compustat data. However, after accounting for capital expenditures, acquisitions, sales, retirements, and depreciation, residual changes in PP&E are about as large as the explained changes and constitute a substantial fraction of the variation in the series.

¹⁷The data on existing home sales are from the National Association of Realtors.

¹⁸Maksimovic and Phillips (2001) is an important exception.

the correlation between volume and prices or returns is positive. This is consistent with our finding for capital reallocation, and we conclude that capital reallocation is procyclical.

2.2 Benefits to Reallocation

Intuitively, capital reallocation should be driven by heterogeneity across firms in their ability to use capital productively. Empirically, it appears that capital does flow from less productive firms to more productive firms.¹⁹ Moreover, in the cross section, the gains from reallocation appear higher when productivity differences are larger.²⁰ Our measure is constructed to capture in the aggregate time series what has been shown in the cross section to explain both which firms engage in capital reallocation as well as the gains to capital reallocation. We use measures of the cross sectional standard deviation of capital productivity to measure the “benefits” to capital reallocation.

We formalize this idea in the context of our model in section 3.1. In the model economy, *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.

The micro evidence and the Euler equations of our model suggest that the aggregate degree of productivity dispersion measures the aggregate opportunities for productive reallocation. We study the cyclical properties of our dispersion measures to assess how the benefits to capital reallocation vary over the business cycle. Since no one measure of capital productivity is perfect, we study several measures, namely: the standard deviation of Tobin's q across firms, the standard deviation of invest-

¹⁹For evidence which suggests that capital flows from less to more productive firms, see Maksimovic and Phillips (2001), Andrade, Mitchell, and Stafford (2001), Schoar (2002), and Jovanovic and Rousseau (2002).

²⁰See Maksimovic and Phillips (2001) for evidence which suggests that productivity gains after acquiring used capital are increasing in the difference between buyer and seller productivity, and Lang, Stulz, and Walkling (1989) and Servaes (1990) for evidence which suggests that the gains from mergers and takeovers are larger when targets have low q 's and bidders have high q 's.

ment rates across firms, the standard deviation of total factor productivity growth rates across industries, and the standard deviation of capacity utilization rates across industries.²¹

In this paper, we do not distinguish between capital reallocation across industries and reallocation within industries across firms. In the first case, reallocation may be both physical (a change of use or location) and ownership reallocation, whereas in the second only ownership may change. In both cases, under our assumption that the firm which deploys a unit of capital determines its productivity, the productivity of the capital changes. Although comparing reallocation within and between industries would be interesting, it is beyond the scope of this paper. In fact, 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.²² However, we do know from the literature that reallocation both within and across industries is common.²³ For robustness, we present dispersion measures at different levels of aggregation where possible. 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 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 3 reports the correlation between the cyclical component of

²¹All 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.

²²However, we plan to explore this issue using plant level data in future work.

²³See the references for micro evidence on capital reallocation using plant level data discussed above, as well as the surveys of the merger literature.

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 greater than zero and less than five, the standard deviation of q 's greater than zero, and the difference between the third and first quartiles of q 's greater than zero normalized by the median of such q 's. Concern about measurement error led us to exclude extreme values of q , a common practice in the literature.²⁴ 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. 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 between zero and five and GDP is -0.130 and this series is plotted in Figure 3. Thus, we cannot reject that dispersion in q is acyclical.²⁵

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

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 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

²⁴See, for example, Abel and Eberly (2002) who use a selection criterion which excludes q 's less than zero or greater than five.

²⁵To 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.

reallocation which occurs. We use three measures of the cross-sectional dispersion of productivity growth rates (see Panel B of Table 3). 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.²⁶ The correlation between the cyclical component of sectoral TFP growth dispersion and the cyclical component of GDP is -0.384 using this measure.²⁷ 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.²⁸ 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 4 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 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

²⁶Schuh and Triest (1998) discuss a similar measure of dispersion using this data.

²⁷We 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.

²⁸We thank John Fernald for providing us with their estimates of industry productivity changes.

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 3). The dispersion of capacity utilization is hence countercyclical which, consistent with the results above, suggests countercyclical benefits to reallocation.²⁹

The literature has studied the dispersion of employment growth rates across industries and the dispersion of industry index stock returns and industry index excess stock returns across industries as measures of sectoral shocks. All studies report that these shocks are countercyclical. These shocks can be thought of as alternative measures of the benefits to capital reallocation. 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 finding that dispersion appears countercyclical, suggesting that the benefits to capital reallocation are countercyclical. To be conservative, we will calibrate our model to acyclical dispersion.

²⁹See also the discussion in section 4. Note that the fact that capacity utilization is censored above and below may bias estimates of cross sectional dispersion.

3 Implied Business Cycle Properties of Liquidity

The data suggests the following two facts about capital reallocation: capital reallocation is procyclical while the benefits to capital reallocation appear 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; our imputed cost implies that it is 2.6 times as costly to reallocate capital in recessions as it is on average. We model the cost of reallocation as a standard adjustment cost incurred by the seller when capital is reallocated. The benefit of our modeling strategy is that we avoid measuring difficult quantities such as the amount of adverse selection or the degree of agency problems inherent in endogenous liquidity models directly. As a result we can generate a quantitative estimate of the variation in capital liquidity over the cycle. The cost of our modeling strategy is that the functional form for capital liquidity is exogenously specified. We motivate our modeling choice for capital liquidity in detail in section 3.1.

It does not seem plausible that there is substantial countercyclical variation in the physical cost of reallocation. In fact, any costs measured in terms of foregone output will be procyclical, including the cost of employee time or production downtime. 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, broadly defined, rather than as physical adjustment costs.³⁰ In this sense, we “identify” capital illiquidity from the cyclical properties of our imputed cost.

³⁰In 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. Pulvino (1998) also finds evidence of lower liquidity for real assets in recessions.

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 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 technologies subject to the aggregate resource constraint. The representative agent has standard preferences

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

where C_t is the representative agent’s consumption of the single consumption good, $u(C) = \frac{C^{1-\sigma}}{1-\sigma}$, $0 < \beta < 1$, 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.

The economy has two technologies which both produce the single consumption good.³¹ Capital is technology specific, but can be reallocated from one technology to the other. 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, $R_{1 \rightarrow 2,t}$ and $R_{2 \rightarrow 1,t}$ occurs at the beginning of the period after the productivities 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 new investment. For example, it is faster to buy an existing plant than to build a new one. 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 and by our measure, reallocation occurs most

³¹We use a two technology model to enable computation.

of the time.

The resource constraint for the model economy is

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

where $A_{i,t}$ is the total factor productivity of technology i , $I_{i,t}$ is investment in technology i for the next period, and F is the production function which we assume takes the following form: $F(\hat{K}_i) = \hat{K}_i^\alpha$, $i = 1, 2$, with $0 < \alpha < 1$. 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. In our model, the productivity of a unit of capital is not embedded in the capital, but is instead determined by the technology in which it is deployed. Thus, when capital is reallocated, the new productivity applies.

Capital is illiquid which means that reallocation is costly and moreover capital illiquidity may vary with the state of the economy. The law of motion for each type of capital, for all i and $i \neq j$, is

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

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

where Γ is the reallocation cost function which represents capital illiquidity, δ is the rate of depreciation with $0 < \delta < 1$, and $R_{i \rightarrow j,t} \geq 0$. 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 ($\Gamma(R_{i \rightarrow j,t}, K_{i,t})$). 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 . For simplicity, we have assumed that, besides the one period delay, there are no other costs of new investment.³²

³²We have computed our model with convex adjustment costs of new investment as well. Since

To impute the cyclical properties of capital liquidity from the model, we will need to specify a functional form for the reallocation cost Γ , the stand-in for capital illiquidity. We are interested in using a functional form for this cost which is consistent with the reallocation data and with our a priori intuition regarding how this cost will vary with the amount of capital reallocated. First, the reallocation cost should imply that a positive amount of total reallocation occurs each period, as it does in the data. Since, for computational tractability, we employ a two sector model, the reallocation from technology i to technology j or vice versa equals the total amount of reallocation which occurs. Thus, 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 each period. 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), we use a two technology model in order to incorporate both idiosyncratic and aggregate effects and thus abstract from firm level non-convexities in this paper.³³ Second, we expect that reallocation will be more costly per unit when the total amount of reallocation in the economy is large. The first assets to be reallocated are likely to be assets least affected by illiquidity. As more reallocation occurs, transactions in which assets, buyers, or sellers are more subject to information or agency problems become necessary. Thus, we choose to use a standard quadratic adjustment cost function to model capital illiquidity. This cost is consistent with zero marginal reallocation costs at zero reallocation and with the idea that reallocating an additional unit of capital is more costly when total reallocation is large. The functional form for the reallocation cost is the standard one used in models with adjustment costs on new investment (see Abel and Eberly, this makes reallocation more attractive relative to new investment, it implies a higher average reallocation cost than the one we discuss below. However, the implied variation in this cost is of the same order of magnitude.

³³See, e.g., 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, and Caballero, Engel, and Haltiwanger (1995) and Caballero (1999) for studies emphasizing that non-convexities at the plant or firm level may have aggregate implications.

1994), namely:

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

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.

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. The logarithm of the 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,

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

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. Specifically, we will consider an economy in which $\gamma \equiv \gamma(z_t^a)$, and impute the process for $\gamma(z_t^a)$ which generates a process for total reallocation which matches the empirical one. This completes the description of the model.³⁴

Reallocation is valuable in this model because at the beginning of each period,

³⁴We 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, $C_t, K_{i,t}, \hat{K}_{i,t}, R_{i \rightarrow j,t}, I_{i,t}$, 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.

after the productivities of the two technologies have been revealed, capital can be re-allocated to its most productive use. This can be seen using the first order conditions for the representative agent's problem which imply that:

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

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 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 provides 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

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

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 4. We use standard parameter values wherever possible. The aim is to find the process for capital illiquidity which generates the observed amount and cyclical properties of capital reallocation in a calibrated model which is consistent with the stylized facts about growth and business cycles.³⁵

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 $\sigma = 2$. A model period equals one year. 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 0.0175.³⁶

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. That is, to be conservative, we calibrate the model assuming that sector specific technology shocks are acyclical rather than countercyclical as most of our measures suggest. Thus, our estimate of the amount of variation in the cost of reallocation will be a lower bound, because calibrating the model using countercyclical dispersion would imply more countercyclical variation in the cost of reallocation. Specifically, we assume that aggregate productivity $z^a \in \{+\Delta^a, -\Delta^a\}$ and sector specific productivity $z_i^s \in \{+\Delta^s, -\Delta^s\}$. Both productivity processes are

³⁵See Cooley and Prescott (1995).

³⁶See footnote 34 for a discussion of where growth needs to be accounted for when computing the model. Setting the growth rate equal to zero does not significantly alter the results.

described by a Markov transition matrix of the form

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

To match the frequency of US business cycles, 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. In the model, the standard deviation of the growth rate of either shock is $\sqrt{1 - \pi}2\Delta$. Given our assumption that for either process π equals 0.75, the standard deviation of the growth rate of the process equals the standard deviation of process itself. Thus, the standard deviation of the aggregate productivity process is $\sigma(z^a) = \Delta^a$ and the standard deviation of the technology specific process is $\sigma(z^s) = \Delta^s$. This allows us to calibrate the standard deviation of the productivity shocks directly to their empirical counterparts. We assume that $\Delta^a = 0.015$, implying an annual standard deviation of the logarithm of aggregate total factor productivity of 1.5 percent, consistent with annual data. The cross sectional standard deviation of productivity growth rates across industries in the data from Basu, Fernald, and Kimball (2001) is 5.7 percent. Thus we choose $\Delta^s = 0.057$.

The purpose of the model is to measure the implied variation in the process for capital liquidity, captured by the capital illiquidity parameter $\gamma(z^a)$, which generates a process for total reallocation consistent with that in our data. Since there are two aggregate states in our model, the implied $\gamma(z^a)$ will consist of two values. The two moments we use to pin down the implied $\gamma(z^a)$ are the unconditional average total reallocation normalized by the capital stock (the reallocation turnover rate) and the ratio of total reallocation in booms relative to recessions. We choose to match an unconditional average reallocation turnover rate of 2.5 percent, which is in between the reallocation turnover rates using assets and PP&E to measure the capital stock (see Table 1, Panel B). Since depreciation is 10 percent, this implies a ratio of reallocation to total investment (in new and used capital) of 20 percent. The unconditional average value of γ which generates this reallocation turnover rate is 0.05. The ratio of reallocation in booms relative to recessions in our data is 1.59,

and we will use this measure to pin down the variation in capital illiquidity around its mean of 0.05. We use this ratio of conditional means rather than the correlation between reallocation and GDP because the ratio is less sensitive to our two sector specification.

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

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

and follows a Markov process which is perfectly negatively correlated with the process for aggregate productivity. This parameterization holds the unconditional expected illiquidity constant, independent of Δ^γ . 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 that when $\Delta^\gamma = 0.05$, capital is perfectly liquid in booms.

3.3 Results

We have constructed a model and calibrated it to be consistent with the stylized facts about business cycles and growth. In this section we will find the implied variation in capital illiquidity which generates a reallocation series consistent with the empirical moments described in section 2. In Table 5 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 matching the ratio of total reallocation in booms relative to recessions. In this economy, the expected marginal cost of reallocating capital when productivity is low is 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 the unconditional average

cost.³⁷ Table 5 presents the model results.

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 capital and reallocation to investment ratios. The expected marginal cost of reallocating an additional unit of capital is 0.0025 which represents 0.11 percent of average consumption. With this constant reallocation cost, and calibrated aggregate and sectoral specific shocks, 2.5 percent of capital is reallocated each year and reallocation is 20 percent of investment (where investment is defined as new investment plus reallocation to be consistent with our empirical measure), in line with the empirical ratios in Table 1. This economy has 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 ratio of reallocation conditional on high vs. low productivity is about one and the correlation between log reallocation and log output is basically zero both in levels and turnover rates.³⁸ 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 terms of foregone output 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 $\Delta^\gamma=0.025$ are reported in Table 5. We focus here on the case where $\Delta^\gamma=0.05$ since this case matches the empirical ratio

³⁷Here, by “expected” we mean the cross sectional average given the stationary distribution of capital across sectors.

³⁸The ratio is slightly greater than one due to the income effect of high productivity on the willingness to incur reallocation costs. This induces a slightly negative correlation between log reallocation and log GDP due to the causal effect of the incurred reallocation costs on output.

of reallocation in booms relative to recessions. 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 ratio of reallocation conditional on high vs. low productivity of 1.56, very close to the empirical ratio of 1.59. The correlation between log reallocation and log output is 0.385, which is lower than the empirical correlation for total reallocation of 0.637. Given the low average reallocation cost derived from the first economy in order to match the empirical reallocation rate, the third economy allows the maximum variation in illiquidity; reallocation is free when productivity is high.

The implied expected marginal cost of reallocating capital when productivity is low is 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 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

4.1 Explaining Business Cycle Variation in Capital Liquidity

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 likely to be more credit constrained and hence 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 (2004). 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 is less risky investment, which results in fewer “non-informational” reasons for trade. Hence the secondary market is more subject to adverse selection in bad times.

In our opinion, variation in liquidity, or cyclical variation in informational and contractual frictions, is the most convincing interpretation of the joint observation of procyclical capital reallocation and countercyclical benefits to reallocation. However, other explanations may be consistent with our findings, and we believe that this joint observation is of independent interest. We focus our discussion on possible “technological” explanations for our findings. 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 percent compared to 23

percent 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.

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. However, note that the direct effect of an increase in the dispersion of productivity in recessions is to increase opportunities for productive reallocation. The indirect effect of uncertainty on individual firm investment or disinvestment would have to overwhelm the direct effect for increased dispersion to actually reduce reallocation.³⁹

Third, one could argue that reduced capacity utilization in recessions might mean that it is not in the interest of productive firms to purchase unproductive firms thereby adding capacity. However, note that overall capacity does not change when the capital is purchased; thus the more productive firm may simply be able to deploy the existing capacity more productively. Note also that aggregate capacity utilization is not much lower in recessions than in booms. We find that the ratio of the mean capacity utilization conditional on GDP being above trend to that when GDP is below trend is 1.04, i.e., close to one. In contrast, the business cycle variation in the dispersion of capacity utilization across sectors is much more pronounced. The ratio of the average cross sectional standard deviation in capacity utilization when GDP is above trend to that when GDP is below trend is 0.88.

Finally, note that if recessions are associated with increased relative productivity dispersion, but such dispersion is more temporary than the relative productivity dispersion in booms, we might expect more reallocation in booms. This would also imply that persistent shocks to relative productivity are larger in booms. However, we argue that the dispersion of forward looking measures of productivity such as

³⁹In standard (S, s) models, increasing the variance of the fundamental shock in fact decreases the time between adjustments. That is, the direct effect typically dominates. See, for example, Dixit (1993). However, we are not aware of a study which incorporates stochastic volatility into such a model.

Tobin's q and stock returns are not procyclical. Relatedly, Storesletten, Telmer, and Yaron (2004) find that persistent shocks to labor income are larger in recessions.

4.2 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). However, there are several important differences between our measures of capital reallocation and measures of labor reallocation, specifically the DHS job flows series. We measure capital reallocation in terms of transfers of ownership of capital between firms rather than the physical movement of capital across plants. In contrast, the DHS data measures job flows in terms of the physical movement of jobs across plants. Specifically, DHS consider net changes in employment at the plant level for manufacturing firms only. Moreover, the literature following DHS focuses on the gross job flows series which does not distinguish between reallocation of jobs and net changes in employment. In contrast, our measures of capital reallocation exclude new investment explicitly. Finally, workers may transition through unemployment as they are reallocated to a different job, whereas capital will always be matched to an owner (although the capital utilization rate may vary).

The labor reallocation 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 gross 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 6).

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, as noted above the capital reallocation and gross job flows series are not directly comparable, since the gross job flows series includes the net change in employment while our measure of capital reallocation excludes new investment

and retirements by definition. To enable a better comparison we use a 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 jobs 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 5 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 excess 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, 1988). 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 (2005) argue that recessions reduce cumulative reallocation, which also might be more related to excess rather than gross reallocation. Relatedly, in a recent paper Hall (2005) argues that in recessions, in particular the 2001 recession, job separation rates decline, as do job finding rates and job-to-job transition rates. 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 6).⁴⁰

Thus, we conclude that the different cyclical properties of the capital reallocation measures and gross job flows may be due to differences in measurement, namely the fact that gross job flows include the net change in employment which is strongly countercyclical. The evidence overall seems consistent with positive comovement between capital and worker flows from one productive use to the next. We leave a more rigorous comparison to future work.

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. The fact that capital reallocation is procyclical while the cross sectional dispersion of capital productivity is countercyclical is surprising. Heterogeneity in the productivity of capital across firms and sectors represents opportunities for productive reallocation, and one would expect to observe more reallocation when the benefits to reallocating capital are higher. We use a calibrated model of costly capital reallocation to impute the cost which reconciles these two empirical observations. This cost needs to exhibit substantial countercyclical variation to match the data. Given its countercyclical nature, we interpret this state dependent cost of reallocating capital as “liquidity,” broadly defined, and conclude that capital liquidity appears procyclical. In other words, the informational and contractual frictions which inhibit capital redeployment seem to be much more severe in bad times.

⁴⁰However, the dating of the labor reallocation data, discussed in the appendix, suggests caution when interpreting these results.

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.

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 greater than 0 and less than 5 are standard deviations of q 's weighted by market value for all q 's in that range. We also computed weighted quartiles of q for all positive q 's.

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.

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 .

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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	0.00	236.63
Sales of PP&E	9.16	0.00	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 (1997) 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
Reallocation	0.637 (0.112)	0.511 (0.193)	0.540 (0.139)	0.414 (0.206)
Acquisitions	0.675 (0.122)	0.437 (0.236)	0.566 (0.133)	0.404 (0.207)
Sales of Property, Plant and Equipment	0.329 (0.173)	0.431 (0.184)	0.220 (0.161)	0.377 (0.197)
Existing Home Sales	0.614 (0.204)	0.489 (0.271)	0.605 (0.195)	0.507 (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
Reallocation	1.586	1.164	1.281	1.125
Acquisitions	1.707	1.195	1.598	1.215
Sales of Property, Plant and Equipment	1.326	1.091	1.165	1.086
Existing Home Sales	1.109	1.033	1.132	1.137

Table 3: Benefits to Reallocation

Deviations from trend are computed using the Hodrick and Prescott (1997) 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

Variable	Correlation of Output with	
	HP	LT
Standard Deviation of Tobin's q ($0 \leq q \leq 5$)	-0.130 (0.259)	-0.122 (0.302)
Standard Deviation of Tobin's q ($q \geq 0$)	0.134 (0.122)	0.137 (0.181)
Difference between 3rd and 1st Quartile Divided by the Median of Tobin's q ($q \geq 0$)	0.110 (0.266)	-0.017 (0.296)
Standard Deviation of Investment Rates	-0.145 (0.230)	-0.472 (0.258)

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

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

Table 4: 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			$R_{i \rightarrow j}$			
[3.15 : 0.03 : 3.93]			[0 : 0.01 : 0.55]			

Table 5: Simulation Results

Panel A: Capital, Output, Investment, and Consumption				
Variable	Liquidity Variation Parameter (Δ^γ)			
	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	0.0108	
Panel B: Reallocation				
Variable	Liquidity Variation Parameter (Δ^γ)			
	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				
$E[R z^a = +\Delta^a]/E[R z^a = -\Delta^a]$	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)	0.9974	1.4835	2.5595	
Marginal Costs ($E[\frac{\partial}{\partial R}\Gamma]$)	0.0025	0.0023	0.0020	
Marginal Costs when $z^a = -\Delta^a$ (Relative to Mean)	1.0001	1.4147	2.0000	

Table 6: Reallocation of Labor

Deviations from trend are computed using the Hodrick and Prescott (1997) filter (HP) or a linear trend (LT). Gross 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 absolute value of 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.

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

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

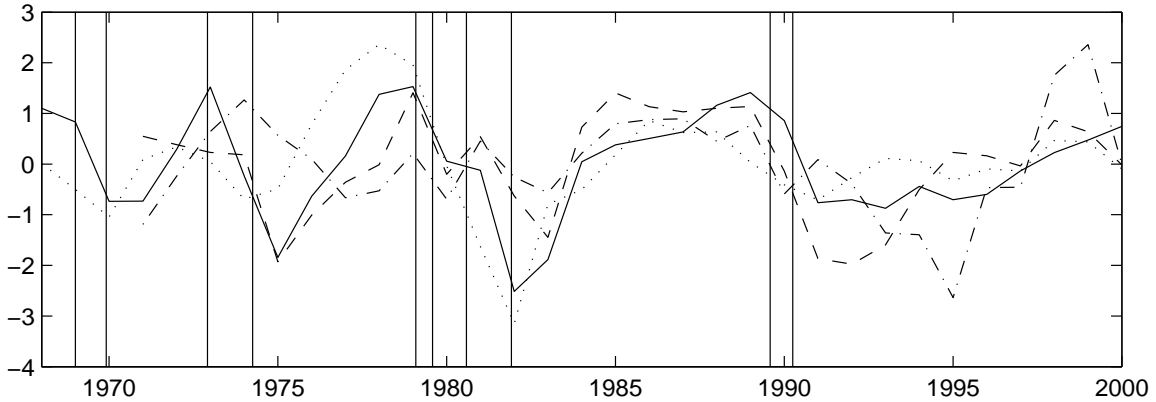


Figure 2: Turnover Rates of Capital over the Cycle

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, dash-dotted line denotes property, plant and equipment sales divided by total property, plant and equipment, and dotted line denotes existing home sales divided by total housing units. Vertical lines denote NBER business cycle dates.

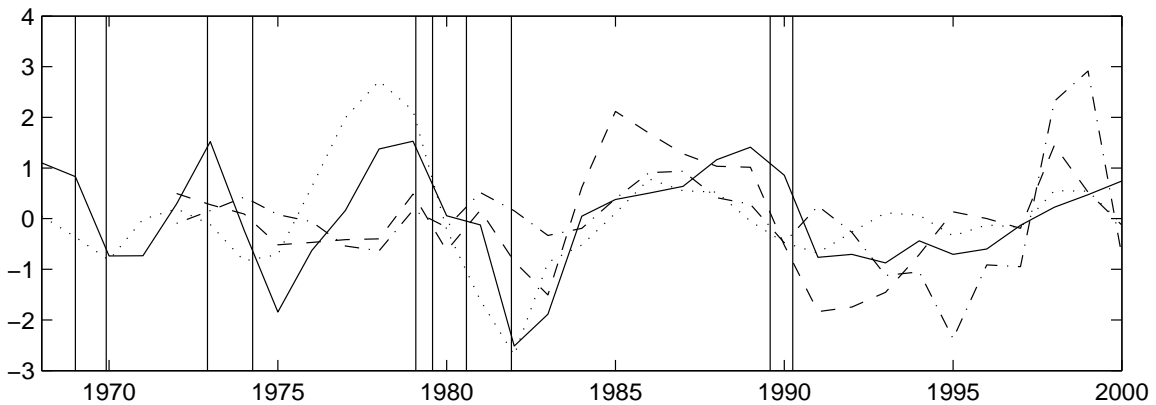


Figure 3: Dispersion in q over the Cycle

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

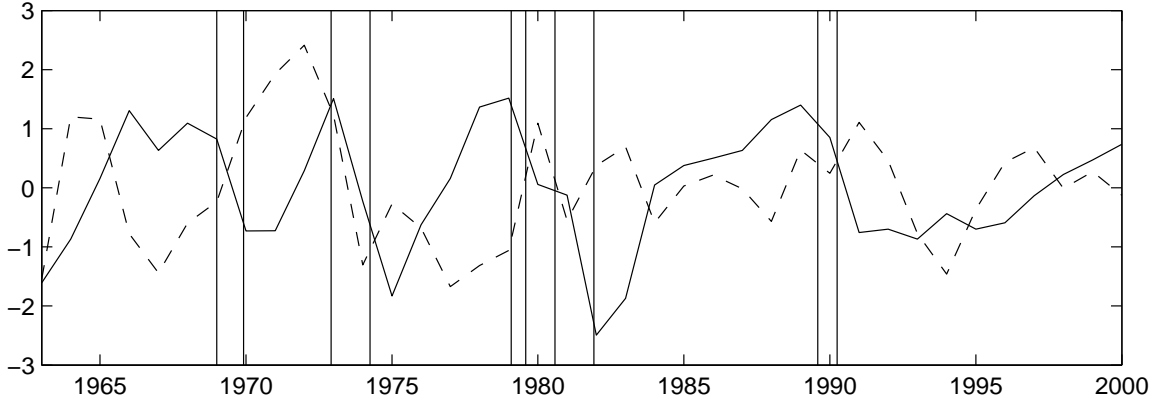


Figure 4: Dispersion in Total Factor Productivity Growth Rates over the Cycle

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

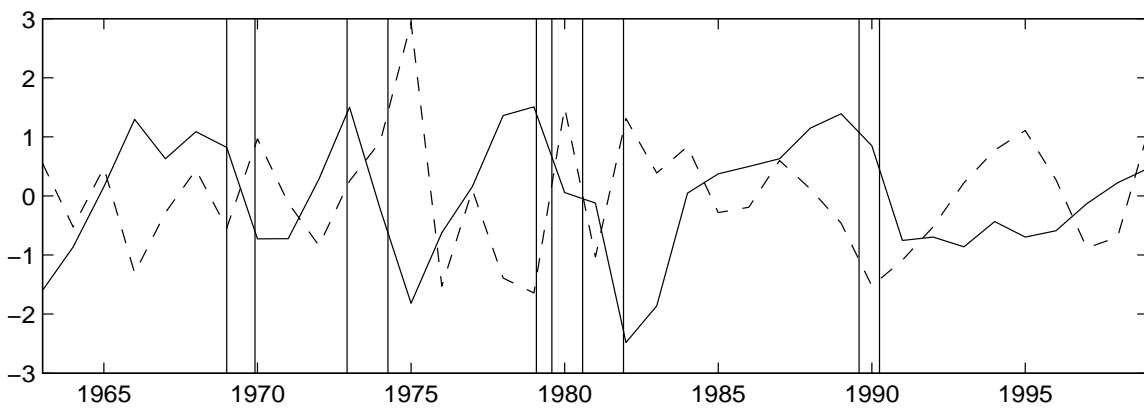


Figure 5: Labor Reallocation over the Cycle

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

