The Cyclicality of Productivity Dispersion*,**

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Abstract

Using plant-level data, I show that the dispersion of total factor productivity levels in U.S. manufacturing is greater in recessions than in booms. This phenomenon is particularly pronounced in durables and primarily reflects a relatively higher share of unproductive firms in a recession. I construct a business cycle model where production requires overhead inputs. In a boom, when overhead inputs are more expensive, only more productive firms enter and only more productive incumbents survive, which results in a more compressed productivity distribution. The model endogenously delivers procyclical aggregate total factor productivity, entry, employment and a countercyclical relative price of durables.

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1 Introduction

How does the productivity distribution across plants change over the business cycle? Knowing the productivity dispersion is necessary to understand the survival conditions for individual plants. To see how these conditions change over the business cycle, I investigate the cyclical properties of productivity dispersion across plants in the U.S. manufacturing sector.

Although some theories of aggregate fluctuations address productivity dispersion, it is not obvious how dispersion moves over the business cycle. One set of models emphasises the process of Schumpeterian "creative destruction" and predicts that productivity dispersion is positively correlated with output. In a recession, when demand is low, unproductive plants exit and are eventually replaced by highly productive plants. In the Schumpeterian world of creative destruction, recessions are "cleansing."[1] On the other hand, an environment where plants compete over common resources – as developed in Melitz (2003) for international trade – has the potential to deliver the opposite result. In a boom, increased demand for production factors raises factor prices. Only more productive plants can afford to pay the higher factor costs, while unproductive plants exit. In a recession, higher productivity dispersion persists in the face of weak competition.[2] In such an environment, recessions are "sullying." Understanding whether recessions are cleansing or sullying sheds light on the question when in the business cycle resources are shifted from unproductive to productive production units.

The existing literature has provided little empirical evidence on the cyclical properties of productivity dispersion, and it is so far not clear whether recessions are cleansing or sullying.[3] The goal of this paper is to address this question. In doing so, I assess the relative importance of cost and demand factors that have a countervailing impact on dispersion as highlighted above.

Knowing the cyclicality of productivity dispersion is important for another reason: A recent body of literature proposes cross sectional risk or uncertainty shocks as a source of business cycles. Christiano, Motto and Rostagno (2009) for example show theoretically that, in an environment with financial frictions, cross-sectional risk shocks may explain up to a quarter of output fluctuations. Such a risk shock, combined with financial frictions, is considered a

[1] Caballero and Hammour (1994, 1996, 2005) formalised the notion of cleansing in a business cycle context which goes back to Schumpeter (1939) and features in a large number of models, among others Mortensen and Pissarides (1994); Campbell (1998); Gomes, Greenwood and Rebelo (2001); Lentz and Mortensen (2008).

[2] Examples of this strand of research are Davis and Haltiwanger (1990, 1992, 1999); Melitz (2003); Ghironi and Melitz (2005); Melitz and Ottaviano (2008); Eisfeldt and Rampini (2006, 2008). The same countercyclical dispersion is consistent with models of reallocation if one accounts for a changing plant size. In a boom, productive plants draw production factors from unproductive plants, which compresses the productivity dispersion.

[3] A number of studies have looked at the productivity dispersion in one or repeated cross sections (see for example Baily, Hulten and Campbell (1992); Bartelsmann and Doms (2000); Syverson (2004) for TFP dispersion in the U.S. Hsieh and Klenow (2009); Moll (2009); Song, Storesletten and Zilibotti (2011) compare the productivity dispersion in developing and emerging economies to the one in the U.S.). Bloom, Floetotto and Jaimovich (2010); Bachmann and Bayer (2011*a*,*b*) document a countercyclical dispersion of productivity *growth rates* and build models where cross-sectional risk shocks cause business cycles. Note that a more spread-out dispersion in productivity *levels* is required in most of these models so that changes in disperion have aggregate consequences.

key candidate for causing the Great Recession of 2008/09 (see among others Christiano, Motto and Rostagno (2009); Chen and Zha (2011)). Their mechanism relies on a more spread-out distribution of productivity levels in a recession, but lacks the empirical micro foundation.[4] In the present paper, I fill this gap and provide empirical evidence for both the presence and magnitude of dispersion cyclicality up to and including the Great Recession.

Using confidential Census data, I estimate plant-level productivity in the U.S. manufacturing sector from 1972-2009. My empirical work establishes three main results: First, cross-sectional productivity dispersion is countercyclical. The distribution of total factor productivity levels across plants is about 10% more spread-out in a recession than in a boom. Second, the bottom quantiles of the productivity distribution are more cyclical than the top quantiles. In other words, the countercyclicality of productivity dispersion is mostly due to changes at the bottom end of the productivity distribution. Third, the countercyclical pattern of productivity dispersion is more pronounced in durable goods industries than in non-durable goods industries. These results were obtained by estimating productivity using the methodology proposed by Olley and Pakes (1996), but they continue to hold when one infers total factor productivity from simple Solow residuals or from using alternative structural techniques. The cyclicality results also hold for several dispersion measures such as the cross-sectional variance, inter-quartile or inter-decile range.

Schumpeterian models typically consider only variation in demand in partial equilibrium, which generates procyclical productivity dispersion.[5] In a boom, when demand is high, unproductive plants survive more easily and vice versa in a recession. This demand channel leads to a cleansing effect of recessions. At face value, such models are at odds with my empirical finding of a countercyclical dispersion. To overcome this inconsistency, I introduce a cost channel into an environment that, without the cost channel, would lead to cleansing in a recession. When plants compete over common resources, such an environment leads to higher cost in a boom, which could make it harder for unproductive firms to survive. Considering the effects of both the demand and cost channel in general equilibrium can overturn the cleansing effect of recessions present in the partial equilibrium Schumpeterian model.

I build a model along the lines of Ghironi and Melitz (2005) in which business cycles are driven by aggregate shocks as in Caballero and Hammour (1994). Plants differ in their productivity and are active in two sectors (durables and non-durables). Production in the durable sector requires a fixed input such as overhead labour or organisational capital. The costs for this fixed overhead input are a crucial determinant of plant profitability. As a result, only plants above a certain productivity cutoff will make non-negative profits and be active in durables. This productivity cutoff, which regulates productivity dispersion, depends positively on the

[4] Chugh (2011) and Chen and Zha (2011) propose similar mechanisms but equally lack the empirical evidence.

[5] A procyclical dispersion results from Schumpeterian models extended by reallocation between surviving firms as in Barlevy (2002).

price of fixed inputs. This feature of my model is closely related to the work by Cooper and Haltiwanger (2006) who aim at identifying quasi-fixed factors in the profit function.

I use my model to study the dynamics of productivity dispersion in booms and recessions. This approach attempts to provide a unified theoretical explanation of both the micro-level dispersion results as well as the typical macroeconomic dynamics. I model aggregate fluctuations as shocks to household preferences that raise aggregate demand. Consider a plant with productivity exactly equal to the cutoff productivity. An increase in demand increases profits. At first sight, additional profits benefit the plant at the cutoff as in Caballero and Hammour (1994). However, higher profits also increase entry. A larger number of plants raises aggregate demand for production factors. In particular, the price of overhead factors rises. This hurts the plant at the cutoff, because it may no longer be able to cover overhead cost. If that is the case, this plant will no longer be active in durables and the productivity cutoff will be higher, resulting in a more compressed productivity distribution in a boom. My mechanism for cleansing in booms is a variant of what Lucas (1978) developed in a growth setting: As the economy grows, fixed entrepreneurial inputs become more expensive, so that the least productive units exit.

My model is hence capable of replicating the three main empirical findings: The changing truncation makes the dispersion countercyclical (Result #1), it operates at the bottom end of the distribution (Result #2) and predominantly in durable goods industries (Result #3). The crucial feature to deliver the above results is the fixed factor and its procyclical price. In reality, there exist a wide array of fixed input factors such as managerial labour, organisational capital, supply chains or technical know-how. In this paper, I model the fixed factor as managerial labour input and present empirical evidence for both its presence and procyclicality. As for the former, higher fixed inputs in durable than in non-durable production will show up in a production function estimation as higher returns to scale. I estimate returns to scale at the plant level and find that they are higher in durable than in non-durable goods industries.[6] This finding lends support to my assumption of fixed factors playing a more important role in durables than in non-durables.

Although the model was constructed with the objective of understanding the business cycle properties of productivity dispersion, other implications of the model have support in the data. For example, the productivity cutoff, and hence average productivity in durables, is procyclical, which results in a countercyclical average relative price of durables. The countercyclicality in the price of durables has been widely noted, and my model appears to provide a novel explanation for that phenomenon.[7] This explanation rests on endogenous selection of more profitable plants

[6] This difference in returns to scale estimated on the plant level confirms the findings of Burnside (1996) and Harrison (2003) who estimated returns to scale on the sectoral and sub-sectoral level.

[7] There has been a long and heated debate about different explanations for this fact. Probably the most relevant strand of research in this area is the investment-specific technological change literature. An alternative strand of research puts increasing returns to scale (in durables) at the heart of a countercyclical relative price of durables. See for example Murphy, Shleifer and Vishny (1989); Benhabib and Farmer (1996); Hall

into durables in a boom. In addition, the model endogenously predicts that aggregate TFP is procyclical although the source of fluctuations in my model is not disturbances to aggregate total factor productivity. This happens because, in a boom, the underlying productivity dispersion is truncated at the bottom.[8] The model is also consistent with procyclical employment and firm entry. Lastly, the truncation also implies that the cross-sectional distribution of rates of return for firms active in durables is more compressed in a boom. This conforms well with the finance literature that finds that dispersion in the cross section of stock market returns is countercyclical, see for example Heaton and Lucas (1996); Storesletten, Telmer and Yaron (2004); Campbell et al. (2001).

The empirical part of my paper is closely related to the work by Bloom, Floetotto and Jaimovich (2010); Bachmann and Bayer (2011*b*). They document countercyclical dispersion of productivity *growth rates* (the latter on the firm level). To answer whether recessions are cleansing or sullying requires to know the dispersion in productivity *levels*. The same is true about models where risk shocks combined with financial frictions lead to a recession as in Christiano, Motto and Rostagno (2009). Davis and Haltiwanger (1990) document cyclical patterns in employment dispersion across plants. My theoretical model is a general equilibrium version of the seminal work by Caballero and Hammour (1994) extended by a non-convex production technology as in Ghironi and Melitz (2005). Syverson (2004) has examined a similar model in different geographic markets.

The paper is organised as follows: Section 2 describes the data, the econometric strategy and documents the empirical findings. The empirical patterns define the puzzle that cannot be explained in existing models with aggregate disturbances. This is the theoretical challenge that is to be explained in Section 3 which lays out the model. The goal of the model is to provide a unified theoretical explanation of both the micro-level dispersion results as well as the typical macroeconomic dynamics. Section 4 concludes.

2 The empirics of productivity dispersion

2.1 Data

I use confidential establishment-level[9] manufacturing data collected by the Census Bureau which comprise the Annual Survey of Manufactures (ASM), the Census of Manufactures (CMF), the

(1990); Harrison (2003). Greenwood, Hercowitz and Krusell (1997, 2000) have proposed exogenous fluctuations in investment-specific technologies to explain both a countercyclical relative price of durables and fluctuations in macroeconomic aggregates. Fisher (2006) and Justiniano and Primiceri (2008) find that a large share of the volatility reduction of macro aggregates is due to a reduction in volatility of investment-specific disturbances.

[8] This implication appears in a number of models featuring productive heterogeneity on the micro level, see for example Lagos (2006); Hsieh and Klenow (2009); Moll (2009).

[9] Census defines an establishment as a business location whose primary activity is production. In manufacturing, this can usually be thought of as a production plant.

Plant Capacity Utilization Survey (PCU), the Longitudinal Business Database (LBD) and the COMPUSTAT-SSEL bridge. In addition to these data, I use industry-level data from several publicly available sources: price deflators from the NBER-CES Manufacturing Industry Database (NBER-CES)[10], various asset data from the the Capital Tables published by the Bureau of Labor Statistics (BLS)[11], the Fixed Asset Tables published by the Bureau of Economic Analysis (BEA)[12] and the Industrial Production and Capacity Utilization published by the Federal Reserve Board of Governors (IPCU)[13]. Unless otherwise noted, all datasets are at annual frequency.

From the Census of Manufactures (CMF) and the Annual Survey of Manufactures (ASM) I construct a large dataset of plants in the U.S. manufacturing sector. This panel spans the years 1972-2009 and to my knowledge it is the longest plant-level data set of a significant sector of the U.S. economy. This period contains six NBER recessions (including the most recent "Great Recession" 2008/09) which allows me to study productivity dispersion over several business cycles. Every year, there are about 60k observations which covers a much larger fraction of plants than other micro-level firm datasets. Also, it covers not just publicly traded firms as in COMPUSTAT which could potentially exhibit different productivity dispersion dynamics than privately held firms. This comparatively broad coverage reduces the risk of misleading conclusions that are based on the specificity of the sample.

I use the price deflators in the NBER-CES manufacturing data to get real quantities of output, materials and energy.[14] Furthermore, I combine this panel with the LBD and the COMPUSTAT-SSEL bridge which helps me to identify additional plant characteristics. The LBD contains information about the birth and death year of all plants in the economy while with the COMPUSTAT-SSEL bridge the CMF/ASM panel can be linked to the COMPUSTAT dataset. Using these additional datasets I can differentiate further plant charactersitics such as plant age, whether a plant is an entrant, an incumbent, simply idle or an exiter and whether a plant belongs to a firm that is publicly traded, i.e. has access to equity finance. All these characteristics have been theoretically linked to productivity dispersion[15] and with my panel at hand, I can address these aspects.

[10]The NBER-CES Manufacturing Industry Database is a joint program of the National Bureau of Economic Research and the Census Bureau; http://www.nber.org/nberces/.

[11]1987-2008 Capital Data for Manufacturing Industries http://www.bls.gov/mfp/mprdload.htm.

[12]Tables 3.1S, 3.1E, 3.3S, 3.3E, 3.7S, 3.7E, 3.8S and 3.8E at http://www.bea.gov/national/FA2004/SelectTable.asp.

[13]Industrial Production and Capacity Utilization – G.17; dataset compiled by the Federal Reserve; http://www.federalreserve.gov/datadownload/Build.aspx?rel=G17.

[14]Note that these are price deflators on the 6 digit NAICS industry level. Ideally, plant-specific prices are needed, but there is no way to get around this data limitation in the full panel, so my productivity measure contains within-industry price dispersion. This measure is commonly referred to as $TFPR$ (Foster, Haltiwanger and Syverson (2008); Hsieh and Klenow (2009)). In the context of this paper, in turn, revenue productivity is actually the relevant measure for firm survival.

[15]See for example Hopenhayn (1992) and Clementi and Hopenhayn (2006).

Earlier versions of the CMF or ASM have been used before in a number of studies (see for example Baily, Hulten and Campbell (1992); Ábrahám and White (2006); Hsieh and Klenow (2009); Petrin, Reiter and White (2011)). Previous research has typically focused on estimating returns to scale, the persistence of productivity or aggregate productivity growth in one or repeated cross sections.[16] To my knowledge, the present paper is the first attempt to analyse the empirical productivity distribution in U.S. manufacturing at annual frequency and to document the cyclical properties over the horizon 1972-2009. In addition to this new research interest, the data that are used in the present study span not only a longer period, but are also substantially improved (as described in detail in Appendix A) over the versions used in the above-cited research.

With its wealth of information on the plant level, the ASM/CMF panel is an excellent source to assess the dynamics of cross-sectional productivity dispersion. Still, it is not perfect: Census samples large establishments above a certain employee or asset value threshold with certainty, smaller establishments are selected with probability $p < 1$. Census chooses the sampling probability p such that the inverse reflects the sampling weight, i.e., the number of establishments that the sampled observations is representative for. In my analysis, I weight observations with the inverse of p to roughly replicate the underlying population of all manufacturing plants. Omitting this step would underrepresent small plants which are known to exhibit different dynamics (see for example Gertler and Gilchrist (1994); Moscarini and Postel-Vinay (forthcoming)). I furthermore weigh observations by plant size to avoid small outlier observations unduly driving my results.[17]

A second potential problem is that Census rotates this subsection of small establishments with $p < 1$ in order to maintain a representative sample of the manufacturing sector. This rotation happens in years ending in 4 and 9 and could thus create a quinquennial selection cycle in the productivity dispersion of small firms.[18] I control for this sampling peculiarity in Section 2.4 and results are also displayed in Table 4.

Lastly, I limit my attention to the "ASM establishments" (identified by `ET = 0`) in Census years (years ending in 2 and 7), when, in principle, the entire manufacturing sector is sampled.[19] This step maintains longitudinal consistency and results in a large panel: over 1972-2009, there are about 2.2 million observations in my sample which corresponds to about sixty thousand plants every year.

[16] Petrin, Reiter and White (2011) for example use the estimator developed by Levinsohn and Petrin (2003) to decompose aggregate TFP growth into terms reflecting technical efficiency and reallocation.

[17] Even the dispersion of unweighted productivities is still countercyclcial suggesting that small plants are more volatile than large plants.

[18] This matters a lot if one is interested in the evolution of dispersion of TFP growth rates rather than TFP levels. This is also a problem if one estimates TFP in a way that requires lagged variables.

[19] Note that this procedure also drops all administrative records. These are establishments with less than three employees, so-called "AR establishments," that are not observed, but imputed by Census based on administrative records from IRS. This procedure follows Foster, Haltiwanger and Syverson (2008).

2.2 Productivity estimation

Studying cross-sectional productivity dispersion requires plant-level productivity estimates. A large literature is concerned with the estimation of production functions and productivity. I build on this literature and the methods it developed. This paper follows the vast strand of previous research and assumes a Cobb-Douglas[20] gross output production function on the plant level:

$$y_{ijt} = a_{ijt} + \beta_j^k k_{ijt} + \beta_j^l l_{ijt} + \beta_j^m m_{ijt} + \beta_j^e e_{ijt} \tag{1}$$

where y denotes the log of production, a total factor productivity and k, l, m and e are logged real inputs of capital, hours worked, material use and energy use, respectively. β^k, β^l, β^m and β^e are production function elasticities. The subscript index t denotes time, i the plant which belongs to industry j. Unless otherwise noted, industry denotes one of the 473 6-digit NAICS industries in the manufacturing sector. Note that the production function elasticities are industry-specific reflecting a common technological structure within an industry. Inference on a_{ijt} will be described below.

The preferred specification is gross output rather than valued added. Basu and Fernald (1995) have shown that the value added specification may lead to an upward bias of production elasticity estimates if firms have market power. This upward bias is not present in the gross output specification. The construction of each input and output variable from the raw datasets is described in great detail in Appendix A. At this point, I just want to mention that materials m and output q have been corrected for inventory changes to accurately reflect goods used and produced rather than goods paid for and sold. Otherwise dispersion in inventory adjustment across plants would generate a changing productivity dispersion. Capital inputs are corrected for capital-embodied technical change; since this process is very specific to the asset type, I distinguish between structure-specific and equipment-specific technical change when computing the structure and equipment capital stock. Capital k is the logged sum of both.[21] Lastly, note that both capital and energy are included in the production function. As pointed out by Burnside, Eichenbaum and Rebelo (1995), the capital stock per se is not productive. Rather, it requires energy (fuels or electricity) to be utilised in production. I therefore use some form of energy to proxy for capital services.[22]

[20] Like Lee and Nguyen (2002) I have also estimated a translog production function without much differences in the productivity dynamics.

[21] In a similar spirit, I also tried to distinguish between production and non-production labour, but this distinction does not matter for results.

[22] Alternatively, I used directly observed utilisation rates from the Plant and Capacity Utilisation Survey (PCU) – a small subset of the manufacturing data. This cross check delivers very similar results than using energy to proxy for the used capital stock suggesting that using energy is a good approximation of capital *services*.

Endogeneity and selection Estimating production functions to learn about either returns to scale (β's) or productivity (a) has been the subject of a considerable body of research.[23] My baseline specification employs the estimation technique proposed by Olley and Pakes (1996). The Olley-Pakes method is widely used in the current productivity literature because it addresses two problems: first, an endogeneity problem (contemporaneous inputs in (1) are correlated with productivity a) and, second, a selection problem (plants with a very low productivity a will exit the industry). While previous research has developed several ways to overcome the endogeneity problem, Olley and Pakes propose the only method that overcomes the selection bias from plant exit. Exit is in fact cyclical (see Jarmin and Miranda (2002)), so the selection bias is cyclical too. In my context, a cyclical selection bias could then drive measured cyclical productivity dispersion. Since exit matters a fair amount in business cycles (the average exit rate in my data is 7%), I am worried that this selection bias could be quantitatively relevant, so my preferred method is Olley-Pakes.

Identification and possible problems The Olley-Pakes method relies on three main assumptions: First, productivity is a first-order Markov process. Second, capital in period t is a function of last period's capital stock and investment; k_{ijt} is hence predetermined while all other inputs are chosen in time t after productivity a_{ijt} is known. Third, investment is strongly increasing in productivity. While the Olley-Pakes method looks like the best-suited approach in the context of this paper, it is not free of problems. The assumption that investment is strongly increasing in productivity will easily be violated in the presence of non-convex adjustment costs which lead to lumpy investment; those observations (with $i_t = 0$) have to be omitted. Although this is a valid concern, it is fortunately not a very pressing problem in my data (the share of observations with $i_t = 0$ is about 15%).

A second downside of the Olley-Pakes method is the assumption that technical efficiency differences are the only factor underlying profitability differences. But it is plausible to think that, in a response to a (firm-specific) demand shock, the firm raises prices rather than production. Prices on the micro level are not available to me, so my productivity measure will be contaminated by within-industry price dispersion. Mapping my baseline specification to the observables in the data, I can write

$$y_i = a_i + \beta^k k_i + \beta^l l_i + \beta^e e_i + \beta^m m_i \tag{1}$$

$$\Leftrightarrow p_i - \overline{p} + y_i = \underbrace{\overbrace{a_i}^{TFPQ_i} + (p_i - \overline{p})}_{TFPR_i} + \beta^k k_i + \beta^l l_i + \beta^e e_i + \beta^m m_i \tag{1'}$$

[23]See for example Hall (1990); Basu and Fernald (1995, 1997); Benhabib and Farmer (1996); Burnside (1996); Harrison (2003) in the macro literature and Blundell and Bond (2000); Olley and Pakes (1996); Levinsohn and Petrin (2003); Ackerberg, Caves and Frazer (2006) in the Industrial Organisations literature.

The value of production that I observe in the data is the left hand side of equation (1'), so the resulting Olley-Pakes estimate will be $TFPR_i = a_i + p_i - \overline{p}$, an object commonly called "revenue productivity" or profitability (see Foster, Haltiwanger and Syverson (2008); Hsieh and Klenow (2009)) which is not to be confused with technical efficiency, $TFPQ_i = a_i$. As Foster, Haltiwanger and Syverson (2008) mention, it is $TFPR_i$ which matters for plant survival rather than $TFPQ_i$. To answer whether recession are cleansing or sullying, the central question of the present paper, $TFPR_i$ the right dispersion measure to look at. Although I am unable to identify dispersion in technical efficiency, I am still able to identify the (revenue) productivity measure that is relevant in this context.

Nevertheless, I want to make sure that my results are not specific to the structural setup of the Olley-Pakes method with its assumptions about investment monotonicity and timing. In Appendix C.3, I infer productivity from Solow residuals and find that the dispersion dynamics of Solow residuals are preserved.

Constructing the dispersion measure Plant-level total factor productivity is jointly estimated with returns to scale in the above procedure. It corresponds to a_{ijt} in equation (1). The object of interest is the cross sectional dispersion of a_{ijt} within each of the 473 industries. I want to collapse these 473 dispersion measures into one statistic that reflects the average dispersion in the manufacturing sector. In order to avoid certain outlier industries dominating this representative measure, I correct dispersion in every industry by some industry characteristics. These corrections are described in detail in Appendix B.1, here is a brief overview: First, I correct industry dispersion for an industry-specific growth trend.[24] The remaining portion is denoted by z_{ijt}; changes in the dispersion of z_{ijt} will reflect business cycle changes around the long-run dispersion trend. Lastly, I recenter z_{ijt} and scale it by its long-run standard deviation σ_j[25]. The resulting normalised industry dispersion is defined as:

$$Sd_{jt}\left(\frac{z_{ijt} - \overline{z}_j}{\sigma_j}\right)$$

To organise my results, I report the dispersion of the median industry[26] for each period t; one measure for non-durable manufacturing ($Disp_t^n$), one for durable industries ($Disp_t^d$). The split into non-durables and durables is motivated by the different time series properties of neutral and

[24] Otherwise industries with very strong or very weak long-run productivity growth will essentially drive my results.

[25] Otherwise, industries where productivity is very spread-out in general like cement will dominate my results. In contrast to correcting for the long-run growth and the scaling by long-run standard deviation, additionally taking out the long-run skewness hardly makes a difference suggesting that higher-order moments do not matter as much.

[26] Considering the mean dispersion across industries rather than the dispersion of the median industry leads to basically the same results.

investment-specific technological progress (see Greenwood, Hercowitz and Krusell (1997); Fisher (2006)). If productivity behaves differently in non-durables and durables on the aggregate level, productivity dispersion dynamics on the micro level, too, might be different.

$$Disp_t \equiv Median_t \left[Sd_{jt} \left(\frac{z_{ijt} - \overline{z}_j}{\sigma_j} \right) \right] \tag{2}$$

2.3 The empirics of cross-sectional productivity dispersion

I now turn to the results of the empirical investigation. Recall that $Disp_t$, the typical within-industry dispersion of productivity levels, will decrease in a recession if strict cleansing would take place, while $Disp_t$ will increase in a recession if recessions are sullying. The two time series $Disp_t^n$ and $Disp_t^d$ as defined in (2) for both non-durables and durables are plotted in Figure 1 and their time series properties are displayed in Table 1. One can easily see that dispersion fluctuates over time. In fact, it is almost as volatile as durable production (i.e. investment goods) and almost three times as much as GDP. Dispersion in durables is slightly more volatile than dispersion in non-durables (about 1.3 times as volatile) which is not surprising given the overall larger fluctuations in the durables than in non-durables. Dispersion in durables is also more more persistent (autocorrelation 0.34) than dispersion in non-durables (autocorrelation 0.07).

Table 1: Productivity dispersion: Summary statstics

Variable X	Corr(X_t, X_{t-1})	σ(X)	$\frac{\sigma(X)}{\sigma(Y)}$	$\frac{\sigma(X)}{\sigma(GDP)}$
$Disp_t^n$	0.069	0.043	1.662	2.002
$Disp_t^d$	0.341	0.053	0.889	2.487
Y_t^n	0.409	0.026	1	1.204
Y_t^d	0.394	0.060	1	2.798
GDP_t	0.505	0.021	–	1

Note: Y_t^n denotes the output of non-durable, Y_t^d that of durable manufacturing. They were obtained from the NBER-CES manufacturing database by dividing the value of shipments (`VSHIP`) by the price deflator (`PISHIP`) for each industry and summing up the resulting real output within all non-durable manufacturing industries (NAICS 311111-316999 and NAICS 322111-326999) to obtain Y_t^n; analoguous procedure for durable output Y_t^d (NAICS 321111-321999 and NAICS 327111-339999). GDP is obtained from the NIPA tables by dividing nominal gross domestic product by the GDP deflator. All variables haven been HP-100 filtered.

Result 1: Productivity dispersion is countercyclial

Figure 1 displays the HP filtered residuals of logged $Disp_t$ measure defined in (2), that is, one can interpret the values as percentage deviations of dispersion from its non-linear trend. The main objective of this paper is to study if the business cycle has an impact on the productivity

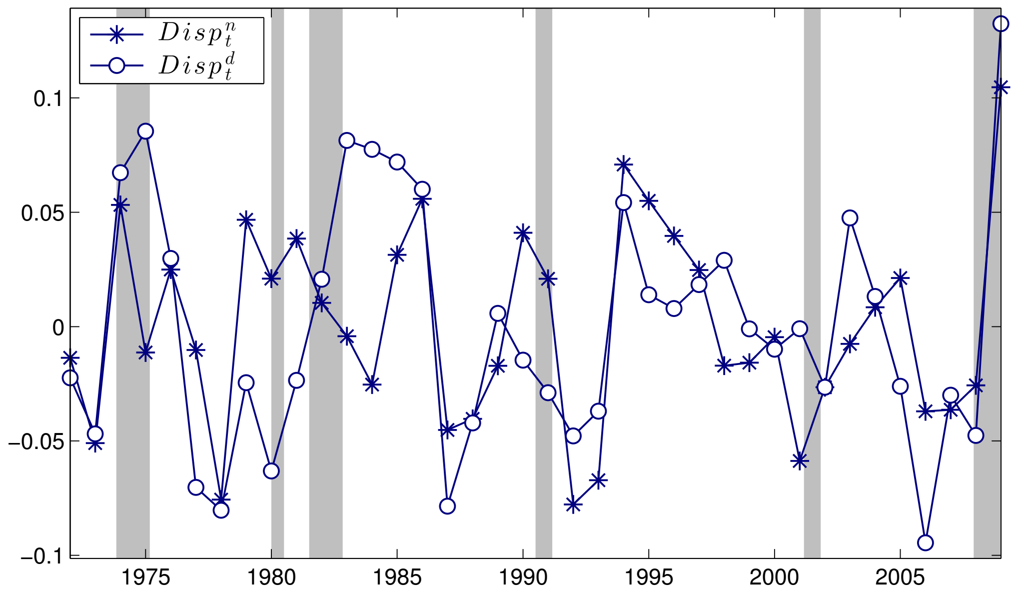

Figure 1: Dispersion in productivity levels

Note: Time series plot of the cyclical components (HP-100 filtered annual time series) of productivity dispersion in non-durable goods producing (stars) and durable goods producing (circles) manufacturing. The dispersion measure is as defined in equation (2). Shaded bars denote NBER recessions.

distribution as predicted by cleansing or sullying theories described in the introduction. The basic cleansing theories would predict that dispersion should decrease in a recession and expand in a boom. But even a casual glance at Figure 1 indicates that most peaks in productivity dispersion coincide with recessions as defined by the NBER (indicated as shaded bars). This looks especially true for the early recessions in the sample: 1974, 1980, 1982 and again – and most strongly – in 2008/09. As Figure 1 shows, the productivity distribution in durables increases by 6.7% (about 1.4% in non-durables) on average in the six NBER recessions in the sample. The increase in dispersion is strong in the 1974 and 1980/82 recessions: From the previous peak to the trough of the recession dispersion in durables increases by 13% and 16% respectively. During the 1990's and 2000's recessions, dispersion does not increase as much and is not as correlated with the cycle as before. In the "Great Recession" of 2008/09, however, the dispersion increase is the largest ever and pervasive through durables and non-durables: at the bottom of the recession in 2009, the distribution is about 20% more spread-out than at the peak in 2007. This shows that risk shocks that have recently been proposed as a business cycle driver (Bloom (2009); Bloom, Floetotto and Jaimovich (2010); Christiano, Motto and Rostagno (2009); Chen and Zha (2011)) might have a prominent role in explaining the latest recession.

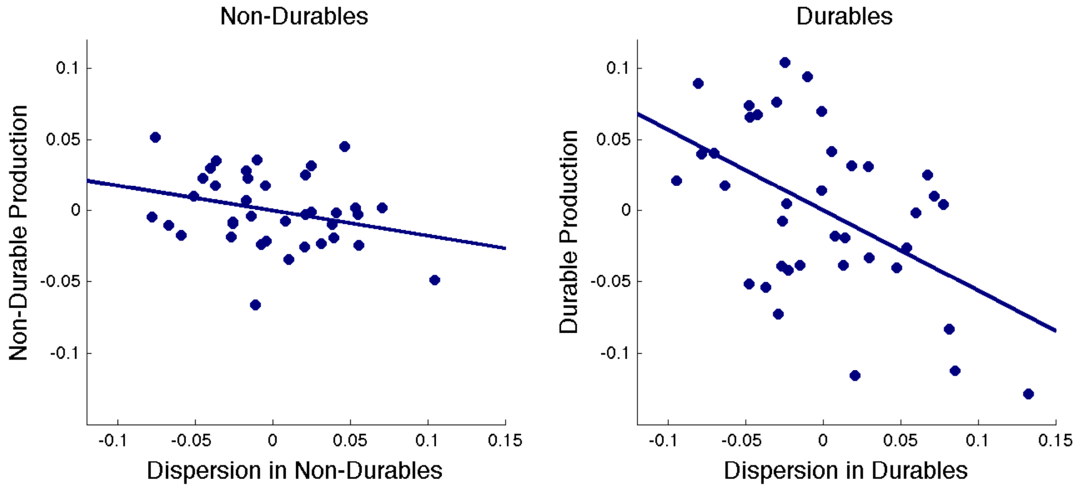

Figure 2: Plot of productivity dispersion and output variations

To my knowledge, this is the first evidence of a more spread-out distribution in productivity levels, thus providing the empirical foundation for the models proposed by these authors.

To formalise the evidence on cyclicality, I correlate the business cycle components of output and dispersion. The resulting scatter plot in Figure 2 shows the negative relationship between production (in durable and non-durable manufacturing respectively) and productivity dispersion. The negative relationship is pervasive but more pronounced in durables – a fact that is confirmed in the Correlograms (displayed in Figure 4). In durable manufacturing, the correlation between output and productivity dispersion is -0.503 and statistically significant at the 95% level. While the correlation between output and productivity dispersion in non-durable manufacturing is negative (-0.293) it is only borderline significant.

Below, I will display the results of several robustness checks. First, I will check if various measures of productivity dispersion such as the inter-quartile range, the variance etc. are countercyclical as well. Second, I will check if dispersion is still negatively correlated with various output measures (manufacturing output, GDP) and different filtering techniques.

Result 2: Unproductive units drive dispersion dynamics

As shown above, the productivity distribution as a whole is negatively correlated with output. This result means that the distribution is *more dispersed* in a recession. This pattern could be explained by the overall distribution fanning out as conjectured by Davis and Haltiwanger (1990). Alternatively, this countercyclicality is consistent with most movements happening at the top of the distribution (as in Gabaix (2011))[27] or at the bottom of the distribution (as in Ghironi and Melitz (2005)). To that end, I look at the behaviour of individual quantiles over recessions.

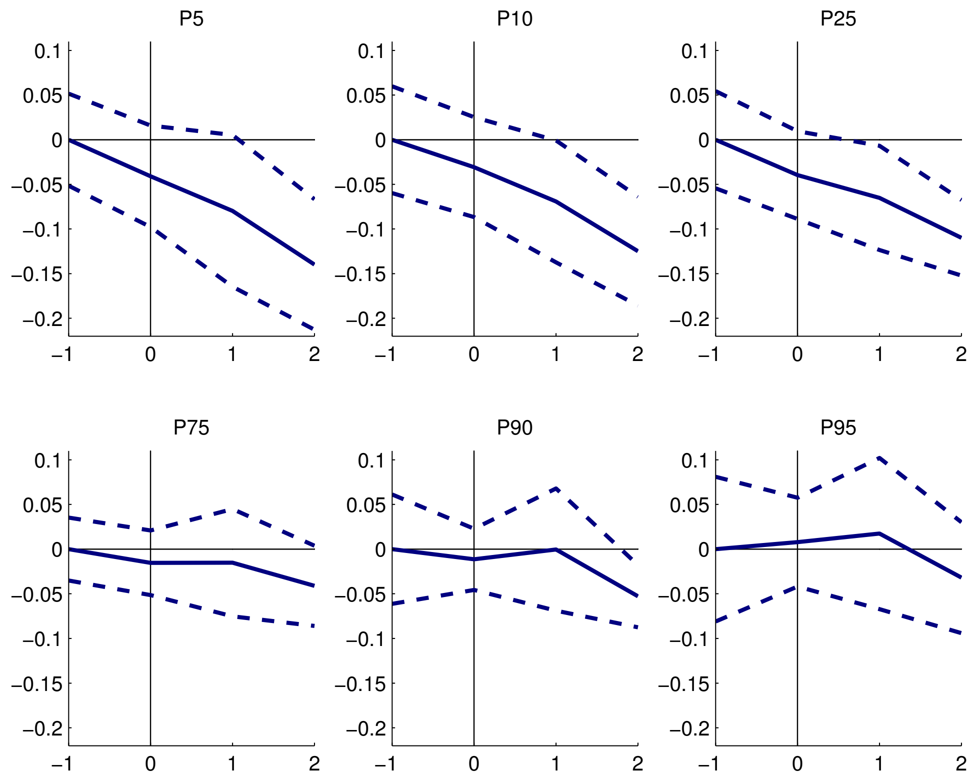

Figure 3: Behaviour of quantiles over NBER recessions

Note: Each panel displays the behaviour of the indicated quantile over NBER recessions. The graphs are obtained by cutting out a subsample (a "worm") of the time series that starts one year before the onset of a NBER recession (denoted by -1) and lasts until years after the onset of a recession (denoted by 2). Solid lines denote the mean of each "recession worm," dashed lines are the standard deviation over the five recessions.

The cleansing view postulates a tougher truncation at the bottom end of the productivity distribution in a recession, i.e. one should see the bottom quantiles picking up in a recession. Figure 3 paints a different picture, however. First, it is predominantly the bottom end of the productivity distribution that changes in a typical NBER recession. Second, these plants *decrease*, i.e. the unproductive tail of the distribution becomes even less productive. This means that the unproductive surviving plants tend to be less efficient in recessions than in booms. The

[27] Gabaix (2011) looks at firm- rather than plant-level data. So it is plausible that some very large high-productivity firms dominate dynamics.

most productive plants in the cross section, in contrast, barely change their productivity over the business cycle. The strong dynamics at the bottom end of the productivity distribution are consistent with the view that a truncation is changing over the business cycle. Such a truncation has been proposed in a number of models: see Caballero and Hammour (1994); Melitz (2003); Melitz and Ottaviano (2008) just to name a few. The evidence that lower quantiles tend to be procyclical suggests that this truncation is *higher* in a boom than in a recession. This result is inconsistent with the view proposed in Caballero and Hammour (1994) that first, the productivity dispersion is procyclical and that, second, the truncation should be higher in a recession. The latter implies that the lower quantiles are countercyclical rather than procyclical. Result 2 conforms well with findings in the literature on product-level pricing. Recall that my productivity measure is revenue productivity which contains the ratio of plant-level to industry-level prices. Berger and Vavra (2011) find that price dispersion is countercyclical which comes predominantly from prices decreases at the lower tail of the distribution rather than price increases at the top end.

Result 3: The dispersion in durables is stronger than in non-durables

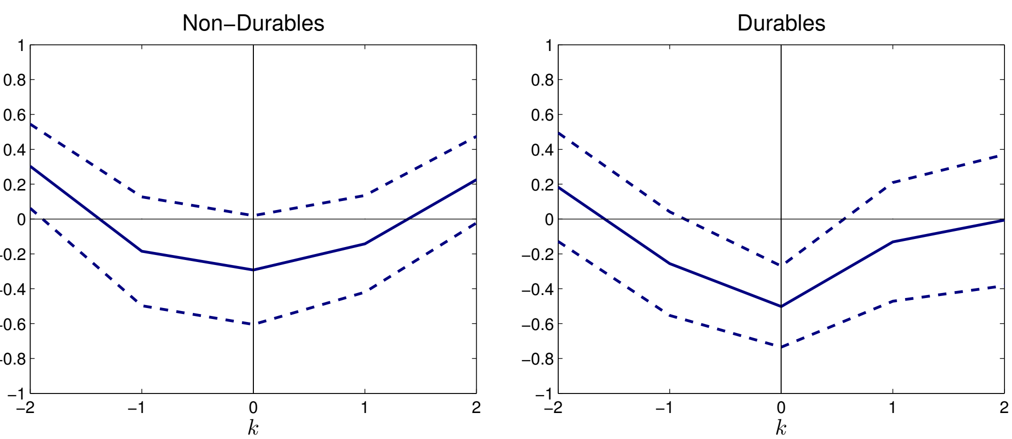

Figure 4: Cyclicality of productivity dispersion

Note: Correlograms of the cyclical components (HP-100 filtered annual time series) of output and productivity dispersion in non-durable (left) and durable (right) goods producing manufacturing respectively: $Corr(Y_t, Disp_{t+k})$. The construction of productivity dispersion is detailed in Appendix B.1. Dashed lines denote 95% confidence intervals computed using GMM controling for autocorrelation and heteroscedasticity à la Newey and West (1987).

The results of the correlations between output and dispersion in the two sectors is displayed in in Figure 4 and Table 2. As we can easily see from those graphs, the productivity dispersion in more pronouncedly and significantly countercyclial in durables than in non-durables. The estimated contemporaneous correlation is -0.502 with a standard error of 0.119. This makes the result significant at the 95% level. This negative correlation is also present – albeit weaker – with a one-year lead suggesting that upshots in dispersion predate contractions. The correlation is slightly less negative and the error bands wider, but the negative correlation is still significantly different from zero at the 90% level.

TABLE 2: CYCLICALITY OF PRODUCTIVITY DISPERSION

Lead/Lag in years	Correlation of output and dispersion in ... Non-Durables	Durables
-2	0.303**	0.183
	(0.123)	(0.159)
-1	-0.185	-0.256*
	(0.159)	(0.152)
0	-0.293*	-0.502***
	(0.159)	(0.119)
1	-0.143	-0.131
	(0.142)	(0.174)
2	0.226*	-0.006
	(0.127)	(0.192)

Note: *, **, *** significantly different from 0 at the 10%, 5%, 1% level, respectively. Dispersion measures defined analogously to equation (2); description of standard errors see Figure 4.

In non-durables goods industries, the overall cyclicality pattern is similar, but with a correlation of -0.293 weaker and only significant at the 90% level. Also, it is far from being countercyclical at several leads and lags. The standard error bands are so much wider than in the durable goods industries that it is impossible to reject the null hypothesis of no correlation at the 95% level or even the 90% level. This probably weighs more importantly: While the dispersion dynamics in durables are significantly countercyclical, the dynamics of dispersion in non-durables are not. This is the second key result of the empirical work on productivity dispersion.

Results 1-3 taken together have an important implication: The countercyclical dispersion is predominantly driven by changes at the bottom tail. If one were to aggregate up micro-level productivity, aggregate productivity would then be *endogenously* procyclical.[28] Viewed through the lens of a real business cycle model, this is an empirical micro foundation of technology shocks. Since I find the micro-level dispersion dynamics to be more pronounced in durables, Results 1-3 can be combined to an empirical micro foundation of technology shocks that are *specific to the production of investment goods*. Investment-specific technological fluctuations

[28]Keep in mind that I used the Census sampling weights and firm size when computing the cross-sectional standard deviation in (2). This is important when thinking about aggregates.

have recently attracted attention in the literature as a potential business cycle driver (see Justiniano, Primiceri and Tambalotti (2010, 2011); Fisher (2006)). In Section 3 below, I'll capture this micro foundation theoretically and show how my model can provide a unified explanation of micro-level dispersion dynamics and aggregate technolgoy.

Note that durable and non-durable goods industries are commonly found to differ along another dimension: The estimated returns to scale are higher in durables then in non-durables. This has been found in previous research (for example Burnside (1996); Harrison (2003) who sectoral or sub-sectoral data) and I confirm this result in Appendix C.1 for my plant-level data. Higher returns to scale in durables suggest that unobserved fixed factors are higher in durables than in non-durables. I shall use this finding to motivate higher fixed factors in durable production which are an important driver of cross-sectional productivity dispersion.

2.4 Robustness checks

2.4.1 Alternative dispersion measures

Table 3: Correlation of output and several measures of productivity dispersion

Correlation of output in with cross-sectional...	Non-durables	Durables
A. Olley-Pakes estimate		
Standard Deviation	-0.293*	-0.502***
	(0.159)	(0.119)
Variance	-0.286*	-0.455***
	(0.166)	(0.141)
Inter-quartile range	-0.311*	-0.509***
	(0.179)	(0.130)
Inter-decile range	-0.058	-0.540***
	(0.166)	(0.120)
B. Solow Residuals (see Appendix C.3)		
Standard Deviation	-0.202	-0.490***
	(0.181)	(0.095)
C. Levinsohn-Petrin estimate		
Standard Deviation	-0.172	-0.420***
	(0.321)	(0.115)

Note: *, **, *** significantly different from 0 at the 10%, 5%, 1% level, respectively. Dispersion measures defined analogously to equation (2); description of standard errors see Figure 4.

Up to this point I have only studied the dynamics of the cross-sectional standard deviation. This cross-sectional measure could be entirely driven by a small number of outlier observations. I want to make sure that the countercyclcial dispersion is pervasive throughout the distribution. To this end, I also study the cyclical patterns of other dispersion measures such as the variance, the inter-quartile and inter-decile range. The results are displayed in Table 3 and confirm the previous results: dispersion is strongly and significantly countercyclical in durables, but only weakly and partially signifiant in non-durables. In line with Result 2 (most action comes from the bottom tail) on would expect the countercyclicality to become stronger by looking at the inter-quartile and inter-decile range, a result that is borne out in the data.

2.4.2 Alternative output measures

Table 4: Correlation of Productivity Dispersion and Several Output Measures

Correlation of dispersion in with...	Non-durables	Durables
Production – HP filtered ($\lambda = 100$)	-0.293*	-0.502***
	(0.159)	(0.119)
Production – HP filtered ($\lambda = 6.25$)	-0.273*	-0.511***
	(0.146)	(0.121)
Production growth rate	-0.160	-0.442***
	(0.186)	(0.163)
GDP – HP filtered ($\lambda = 100$)	-0.336*	-0.537***
	(0.172)	(0.122)
GDP – HP filtered ($\lambda = 6.25$)	-0.183	-0.439***
	(0.152)	(0.127)
GDP growth rate	-0.250	-0.413**
	(0.190)	(0.168)
No. of NBER boom quarters/year	-0.209	-0.408**
	(0.171)	(0.163)
Census rotation years dropped	-0.306**	-0.496***
	(0.143)	(0.124)

Note: *, **, *** significantly different from 0 at the 10%, 5%, 1% level, respectively. Description of standard errors see Figure 4.

In addition to checking the robustness across different dispersion measures, I now check the robustness through different output measures. All of these results are displayed in Table 4. So far, output was defined as the production of the respective subsector of manufacturing. While this is the most plausible measure to matter for the productivity dispersion of the surviving plants, manufacturing – though very cyclical – is only one sector in the economy. To check if dispersion dynamics are correlated with the overall business cycle, I correlate dispersion with HP-filtered GDP. Following Ravn and Uhlig (2002), I choose the HP coefficient to be 6.25 rather than the more conventional 100. To avoid the implicit assumptions of any filtering technique, I also look at the correlation of dispersion and output growth rates. All different output measures are negatively correlated with dispersion and the durable-non-durable split is still present.

Lastly, I am concerned about years ending in 4 and 9 when Census rotates the sample of small plants. I am worried that the firms entering the sample in one of those sample rotations could be systematically different in their productivity. In fact, one of the criteria for updating the sample is to maintain a representative size distribution.[29] If large and small plants have different productivity distributions, then this cold artificially change the productivity distribution in years 4 and 9 – all of which (except 1974) are boom years when I find the distribution to be more compressed. When I drop these years from my time series, dispersion is still significantly countercyclial, thus suggesting that the plant selection induced by Census does not distort the underlying dispersion dynamics. More robustness checks are conducted in Appendix B.2.

2.5 Extensive versus intensive margin

The universe of plants is made up of different types of plants each of which has a distinct productivity distribution. The most important types of plants in that respect are entering, incumbent and exiting plants. Most theoretical models predict that exiting plants have lower productivity while entering plants – that typically embody newer vintages – have higher productivity.[30] Previous empirical work has established that entry and exit vary systematically with the business cycle (see Lee and Mukoyama (2011) for plant entry and exit and Davis and Haltiwanger (1990) for job creation and destruction) although the magnitude of entry and exit is debated.

Is the productivity distribution more spread-out in a recession because productivity changes across all plants (intensive margin) or because the composition of plant types systematically changes over the business cycle (extensive margin)? The countercyclical dispersion could result from procyclical entry if the productivity distribution of entrants has similar support to that of incumbent plants but is more concentrated. An analogous argument holds for exit.

One class of models stress the importance of the intensive margin where the productivity of all plants – entering, exiting and incumbent – is more spread-out in a recession. The interpretation of cross-sectional productivity dispersion as risk shocks lies at the heart of the this

[29] In the non-rotation years, Census tries to merely adjust the sample in a way to account for entry and exit. Census attempts to keep the age distribution of plants representative.

[30] This is mostly true for "successful entrants," plants that enter and are productive enough to remain in a competitive environment. "Unsuccessful entrants," in contrast, are plants that enter and are so unproductive that they have to leave immediately.

Table 5: Summary Statistics: Share of plant types

Share of...	Non-Durables	Durables
Entrants	5.5%	5.4%
Exiters	6.2%	6.0%
Idle	0.7%	0.7%
Active	87.6%	87.9%
No. annual obs.	26,510	28,395

view. Another class of models emphasise the extensive margin where cyclical entry and exit are the main driver of productivity dispersion while the productivity of individual surviving plants is fixed (e.g., Caballero and Hammour (1994)). In my sample, entrants and exiters make up about 12% of all observations; this might be strong enough to impact the dispersion dynamics of the entire sample.

To check if compositional bias is driving my results, I split the sample into incumbent plants on the one hand and entering/exiting[31] plants on the other hand. If dispersion dynamics were solely driven by the extensive margin, the sample of incumbent plants would not exhibit dispersion dynamics. If, on the other hand, dispersion dynamics are pervasive throughout all plants, both subsamples should exhibit the countercyclical dispersion.

As Table 6 shows, both groups exhibit similar dispersion dynamics. In the group of incumbent plants, productivity dispersion is countercyclical in durables and (again weakly so) in non-durables. Both volatility and cyclicality among incumbent plants resemble that of the overall sample which one would expect given that incumbents make up 87% of the overall data. The subsample of entrants and exiters, in contrast, is much more volatile than the overall sample. The cross sectional standard deviation fluctuates about four to five times as much as that among incumbent plants. Dispersion among entrants/exiters is also more pronouncedly countercyclical than that among incumbent plants, especially in non-durables which is in contrast to the weak cyclicality of productivity dispersion among non-durables incumbents.[32] Because the countercyclical dispersion is pervasive throughout incumbents, entrants and exiters, we can rule out that productivity dispersion is *solely* driven by compositional changes. Productivity changes along the intensive margin must take place. The much stronger volatility across entrants/exiters, however, suggests that changes along the extensive margin amplify the countercyclical dispersion.

[31] An exiting plant is defined as a plant that is active, but will exit at the end of this period.

[32] Lee and Mukoyama (2011) find that entrants in recessions tend to be more productive entrants in booms. To be consistent with my results about the entire universe of firms, dispersion of exiters and incumbents must be strongly countercyclical. Note that the difference may also stem from the shorter time horizon they are using.

Table 6: Productivity dispersion – extensive and intensive margin

	Non-durables	Durables
A. Volatility		
Full sample	0.043	0.053
Incuments	0.040	0.049
Entrants/Exiters	0.203	0.239
B. Cyclicality		
Full sample	-0.293*	-0.502***
	(0.159)	(0.119)
Incumbents	-0.282*	-0.482***
	(0.159)	(0.132)
Entrants/Exiters	-0.577***	-0.197*
	(0.078)	(0.118)

Note: *, **, *** significantly different from 0 at the 10%, 5%, 1% level, respectively. Volatility is the standard deviation of the dispersion time series. Cyclicality denotes the correlation between manufacturing output and dispersion (non-durable and durable, respectively). Description of standard errors see Figure 4.

3 The model

The empirical work presented in the previous section has established three main results: the cross-sectional productivity dispersion is countercyclical, unproductive plants are the main driver of dispersion dynamics and the countercyclicality is stronger in durables than in non-durables. The standard cleansing of recessions view has trouble addressing the first two facts. The goal of this theoretical section is to develop a business cycle model that is consistent with the empirical findings on the micro level without ruling cleansing out a priori. In contrast to previous research, aggregate rather than idiosyncratic shocks drive business cycles in my model.[33] Given the importance of dynamics at the bottom of the distribution, my model will feature a fixed factor of production as in Melitz (2003); Ghironi and Melitz (2005) which will give rise to a truncation of the productivity distribution from below. The presence of a fixed factor is supported by my estimation of returns to scale (see Appendix C.1). They are higher in durables which suggests the presence of a higher fixed factor in durables; precisely in that manufacturing subsector whose productivity dispersion is most cyclical. I model two sectors

[33]Models that are driven by idiosyncratic productivity shocks are Gabaix (2011); Christiano, Motto and Rostagno (2009); Christiano, Trabandt and Walentin (2010); Bloom, Floetotto and Jaimovich (2010); Bachmann and Bayer (2011*a*,*b*).

– durables and non-durables – to keep the model consistent with the empirical evidence on returns to scale and the cyclicality of productivity dispersion.

The model features endogenous entry in the economy (exit is random) and firm-level heterogeneity in productivity. In the model, I adopt the assumption from Olley and Pakes (1996) that all cross-sectional profitability differences are driven by underlying technological differences (a_i in equation (1')) rather than mark-up differences ($p_i - \overline{p}$ in equation (1')). I am aware that this interpretation of my empirical results is specific in that it ignores possible changes in mark-ups and a varying degree of competition, both of which probably are relevant in the real world. These elements could be added to the model [34], but the more simple model version chosen here is sufficient to explain the empirically observed results.

3.1 Final goods producers

There is a non-durable goods sector (denoted by n) and a durable goods sector (denoted by d), that each produce a homogeneous final good by assembling heterogeneous varieties y_i:

$$
\begin{aligned}
Y_t^n &= \left[\int_{i \in \Omega} y_{it}^{\frac{\sigma-1}{\sigma}} \, di \right]^{\frac{\sigma}{\sigma-1}} \qquad \sigma > 1 \\
Y_t^d &= \left[\int_{i \in \Omega^*} y_{it}^{\frac{\varrho-1}{\varrho}} \, di \right]^{\frac{\varrho}{\varrho-1}} \qquad \varrho > 1
\end{aligned}
$$

where Ω is the set of varieties used in Sector n and Ω^* that of varieties in Sector d. We will later see that $\Omega^* \subset \Omega$. The elasticity of substitution between varieties in the two sectors is allowed to differ. Relaxing the assumption of an identical elasticity of substitution in both sectors allows for the possibility that intermediate firms can price discriminate between final customers.[35] The residual demand curve for each variety in both sectors is identical except for the different elasticity of substitution

$$
\begin{aligned}
p_{it} &= P_t^n \left(\frac{Y_t^n}{y_{it}} \right)^{\frac{1}{\sigma}} \\
p_{it} &= P_t^d \left(\frac{Y_t^d}{y_{it}} \right)^{\frac{1}{\varrho}} .
\end{aligned}
$$

[34] I could introduce imperfections – "wedges" or deviations in the firms' first-order condition as in Hsieh and Klenow (2009) or varying substitutability between products as in Melitz and Ottaviano (2008); Foster, Haltiwanger and Syverson (2008) – that lead to a changing mark-up dispersion across firms when aggregate conditions change.

[35] The degree of substitutability between varieties, σ and ϱ, and thus mark-ups of upstream suppliers is constant. One could add a changing mark-up dispersion to the changing productivity dispersion by introducing varying substitutability to the technology of final goods firms.

Therefore, the price indices in both sectors can be expressed as

$$P_t^n = \left[\int (p_{it}^n)^{1-\sigma} di \right]^{\frac{1}{1-\sigma}}$$
$$\tilde{P}_t^d = \left[\int (p_{it}^d)^{1-\varrho} di \right]^{\frac{1}{1-\varrho}}.$$

It is important to keep track of the two different prices because the relative price of durables, $\frac{\tilde{P}_t^d}{P_t^n}$, will change when economic conditions change.

3.2 Intermediate goods producers

There is a continuum of monopolistic intermediate goods producers, each of which produces a particular variety $i, i \in [0,1]$. For reasons of simplicity they just employ labour.[36] Apart from producing different varieties, each firm is endowed with an idiosyncratic productivity draw, denoted by z_i, upon birth which it keeps for the rest of its existence. Every firm hires labour l_{it} to produce output which it can sell either in Sector n or in both Sectors n and d. The specific characteristic of the durable goods sector is a fixed factor in production. A firm has to pay a cost c_f if it wants to sell its goods there as well. This fixed costs can be interpreted as overhead expenditures for advertising, management or R&D. The formulation of a fixed factor in durables is motivated by the finding that returns to scale in durables are higher than in non-durables. This finding is consistent with the results of previous research (see for example Burnside (1996); Harrison (2003)) and is borne out in my data as well (see Table 10). Note that this result should be interpreted as a *difference* in fixed factors rather than fixed factors being absent from non-durables. *Higher* returns to scale in durables then suggest *higher* fixed factors in durables. Since I am only interested in differences in returns to scale between the two sectors, I keep returns to scale constant in Sector n and add the fixed factor in Sector d which make Sector d look like increasing returns to scale. The production functions for either sector are

$$y_{it}^n = z_{it} l_{it}$$
$$y_{it}^d = z_{it}(l_{it} - c_f)$$

[36] This simplifying assumption could be relaxed at the expense of expositional clarity. It wouldn't change the qualitative results, however.

Firms take nominal wages, W_t, and their demand curve as given. Profit-maximising behaviour leads to the familiar pricing rule[37]

$$p^n_{it} = \frac{\sigma}{\sigma-1}\frac{W_t}{z_{it}}$$
$$p^d_{it} = \frac{\varrho}{\varrho-1}\frac{W_t}{z_{it}}.$$

I define the real wage as the nominal wage in terms of the non-durable output good: $w_t \equiv W_t/P^n_t$ and let the relative price of durables be $P^d_t \equiv \tilde{P}^d_t/P^n_t$. From now on we express every variable in terms of output n, for example profits are $\pi^d_t = \pi^{d\ \mathrm{nom}}_t/P^n_t$. Using the profit-maximising pricing rule we can derive firm output, labour demand and profits in both sectors in terms of wages and aggregate sector sales. Firm profits in the non-durable sector are always positive because firms charge a mark-up over marginal cost and there are no fixed cost. In durables, in contrast the presence of the fixed factor implies fixed cost and thus potentially negative profits. The profit function in durables is:

$$\pi^d_{it}(z_{it}) = \frac{1}{\varrho}\left(\frac{\varrho-1}{\varrho}\frac{z_{it}}{w_t}\right)^{\varrho-1}\left(P^d_t\right)^{\varrho} Y^d_t - w_t c_f$$

The productivity cutoff The fixed cost preclude very inefficient firms to produce for Sector d, i.e., there is a productivity level z^*_t such that profits from producing for Sector d with productivity z^*_t are zero. Solving the above profit function for this cutoff yields

$$z^*_t = \frac{1}{\varrho-1}\left[\left(\varrho\frac{w_t}{P^d_t}\right)^{\varrho}\frac{c_f}{Y^d_t}\right]^{\frac{1}{\varrho-1}} \tag{3}$$

Firms with productivity below the threshold defined in (3) drop out of the production of durables and only produce non-durables.[38] Equation (3) is a key relationship as it regulates the equilibrium distribution of productivity and therefore deserves some discussion. Although there are still endogenous variables contained in this expression, it is instructive to take a close look at it. Unproductive firms with a low z can more easily survive in this environment if the value of their sales is high (high Y^d_t or high P^d_t). Conversely, a downturn poses harsher conditions for unproductive firms that may have to exit. This aspect reflects the view that recessions are weeding out unproductive firms – the "cleansing effect of recessions" (Caballero and Hammour (1994)). Because the cleansing effect emerges due to changes in aggregate demand (to be precise, the value of aggregate demand), I label this channel the "demand channel."

[37]One could add a changing mark-up dispersion by introducing firm-level inefficiencies such as exogenous deviations from first-order conditions.

[38]Alternatively, one could assume firms are just active in one sector and firms below the cutoff would go idle.

In my model, there is a second channel that I label the "cost channel" which has the opposite effect on the productivity cutoff. If the costs for the fixed factor, w_t, are high, it is fairly costly for a firm to operate profitably regardless of its production level. It must hence be productive enough to have a relatively low price and thus attract enough demand to make profits at all. Since real wages are procyclical, a downturn may hence be associated with a *decrease* in the productivity cutoff. In the same way the cleansing effect operates through the demand channel, there is a "permissive effect of recessions" which operates through the cost channel. A decrease in the real wage is permissive in that it allows inefficient firms to stay in the economy. Note that while the cleansing effects of recession literature emphasised the importance of demand, I also consider cost factors in firm survival. It is unclear ex ante, whether the cleansing effect via the demand channel or the permissive effect of recessions via the cost channel would dominate. This depends on the response of real wages to aggregate output and the elasticity of substitution ϱ. The strength of the cost channel is increasing in the elasticity of substitution ϱ. The higher ϱ, the more easily single varieties are substituted against other ones and the lower the mark-up of single firms. In that case, small changes in the real wage have a strong impact on the survival of unproductive firms and the cost channel dominates the demand channel. Higher wages in a boom will then lead to a higher cutoff and a more compressed productivity dispersion.

If single varieties are bad substitutes, however, unproductive firms can more easily survive an increase in real wages. This is because bad substitutability leads to higher mark-ups which in turn allows unproductive firms to pass through the higher wages to final producers. Then the demand channel will dominate the cost channel. Higher aggregate demand in a boom will then lead to a lower cutoff and a more spread-out productivity dispersion.

Are fixed factors more important in durables? The fixed production factor in durables c_f is a non-standard feature of the model (without it, the model essentially collapses to the RBC model). Since it gives rise to the productivity cutoff, it is a key regulator of the productivity dispersion. I motivate the fixed factor in durables with the result of result jointly estimating productivity and returns to scale in (1). If in reality fixed factors are in reality more important in durables, then unobserved fixed factors will bias estimated returns to scale upwards. I present results on the returns to scale in Appendix C.1.

How cyclical are the cost of fixed factors? One criticism against the importance of the permissive effect could be that wages are generally believed to be very sticky. This would greatly dampen the permissive effect. One needs to take a close look at the wage in expression (3): it is the cost of the *fixed* labour input. This fixed labour input can be thought of a place holder for several fixed factors such as managers and rents for structures among others. I focus on the interpretation as a manager. The cyclical behaviour of the cost for this fixed factor is very different than the cost for normal production labour input. To support this claim with empirical evidence, I turn to data on managerial compensation and analyse the cyclicality of their income. The data come from ExecuComp, a database that covers the top executive pay in a large cross section of firms. Their real income growth rate is computed and correlated with the business cycle in Figure 5.

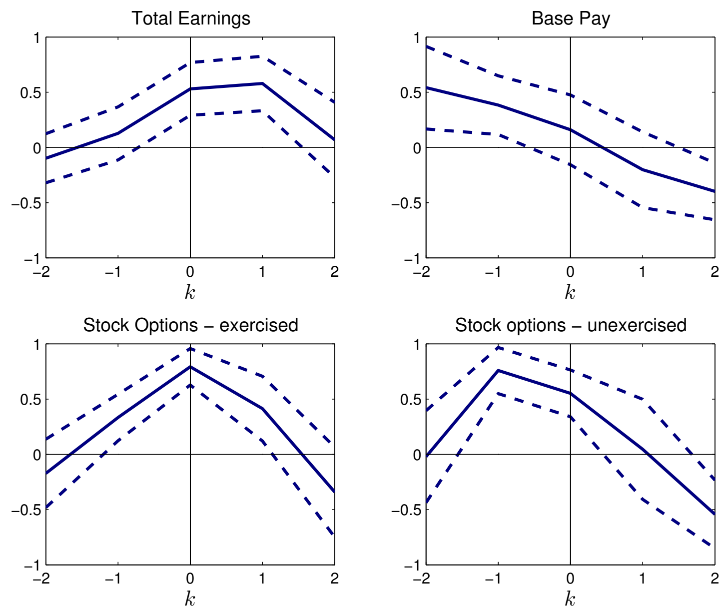

Figure 5: Cyclicality of executive compensation

Note: Correlogram of different portions of executive compensation: $Corr(GDP_t, w_{t+k})$, dashed lines denote 95% confidence intervals constructed as describe in Figure 4. Correlated data are HP filtered residuals of GDP and the aggregate real earnings.

One would expect the managerial wages to be mostly acyclical if they behaved like normal production worker wages. But Figure 5 paints a different picture. All components of managerial compensation – be it base salary, payment in shares or stock options – are pronouncedly procyclical.

3.3 Aggregation and averages

In order to close the model, I need to aggregate firm-level production and employment to the economy-wide level. I can use the above-listed expressions for optimal firm production and employment and use the aggregate production function to obtain aggregate output in both sectors. Keep in mind that I can integrate over all varieties i or over all productivity levels z. If I do the latter, I have to take into account that there is a certain measure of firms active in

Table 7: Components of executive compensation

Compensation Component	Share	Volatility (over time)	$Corr(GDP_t, w_{t+k})$
Base Pay	15.28%	0.102	0.161
Stock Options – exercised	19.39%	0.430	0.792
Stock Options – unexercised	65.32%	0.361	0.552
Total Earnings	100.00%	0.166	0.531

Note: Components of executive compensation are the average share of each component in aggregate earnings. Volatility of each component is the standard deviation over time of HP filtered residuals of aggregate earnings in each category.
Data come from the Compustat – Execucomp (Annual Compensation) database, a panel of top executives in 3,200 firms 1992-2009. Each component of nominal earnings was deflated using the consumer price index to obtain real earnings. Total Earnings (`TDC1`) comprises Base Pay (`SALARY`), the value of exercised stock options (`OPT_EXER_VAL`) and the value of exercisable stock options that were not exercised (`OPT_UNEX_EXER_EST_VAL`).

the economy which is defined as N_t. This measure varies with entry and exit (described below), but in period t it is a state variable. Let the average productivity levels be

$$\overline{z}^n = \left[\int_{z_L}^{z_H} z^{\sigma-1} dF(z)\right]^{\frac{1}{\sigma-1}}$$

$$\overline{z}_t^d = \left[\frac{1}{1-F(z_t^*)}\int_{z_t^*}^{z_H} z^{\varrho-1} dF(z)\right]^{\frac{1}{\varrho-1}}$$

Then we can aggregate intermediate output

$$\begin{aligned}
Y_t^n &= \left[\int y_{it}^{\frac{\sigma-1}{\sigma}} di\right]^{\frac{\sigma}{\sigma-1}} \\
&= \left(\frac{\sigma-1}{\sigma}\frac{1}{w_t}\right)^{\sigma} Y_t^n \left[\int z_{it}^{\sigma-1} di\right]^{\frac{\sigma}{\sigma-1}} \\
&= \left(\frac{\sigma-1}{\sigma}\frac{1}{w_t}\right)^{\sigma} Y_t^n \left[\int_{z_L}^{\infty} z^{\sigma-1} N_t dF(z)\right]^{\frac{\sigma}{\sigma-1}} \\
1 &= \left(\frac{\sigma-1}{\sigma}\frac{1}{w_t}\right)^{\sigma} N_t^{\frac{\sigma}{\sigma-1}} \left[\int_{z_L}^{\infty} z^{\sigma-1} dF(z)\right]^{\frac{\sigma}{\sigma-1}} \\
1 &= \left(\frac{\sigma-1}{\sigma}\frac{1}{w_t}\right)^{\sigma} N_t^{\frac{\sigma}{\sigma-1}} \left(\overline{z}^n\right)^{\sigma}
\end{aligned}$$

Note that the last expression shows that the wage is a state variable because $\overline{z}^n$ is fixed and N_t is a state variable. The wage will change as more firms enter the economy. The fact that wages are completely determined by labour demand only follows from the firm production technology which has constant returns to scale and uses labour only.

As in Melitz (2003) the present economy with heterogeneous firms is isomorphic to one with a measure of N_t representative firms producing with exactly that "average" productivity level $\overline{z}^n$. This average productivity does not change because the underlying productivity distribution does not change over time and any firm will be producing in equilibrium. Accordingly, there is a similar expression of aggregate productivity in Sector d with the only difference that the relevant cutoff is z_t^* rather than z_L. Up to truncation the productivity distribution of firms active in sector d is the same as in Sector n, a feature which shall be explained in greater detail below.

If I parametrise the productivity distribution as bounded Pareto with shape parameter k on support $[z_L, \infty)$, then these expressions have a convenient closed-form solution

$$\overline{z}^n = \left(\frac{k}{k+1-\sigma}\right)^{\frac{1}{\sigma-1}} z_L \tag{4}$$

$$\overline{z}_t^d = \left(\frac{k}{k+1-\varrho}\right)^{\frac{1}{\varrho-1}} z_t^* \tag{5}$$

$$1 - F(z_t^*) = \frac{N_t^d}{N_t} = \left(\frac{z_L}{z_t^*}\right)^k = \left(\frac{z_L}{\overline{z}_t^d}\right)^k \left(\frac{k}{k+1-\varrho}\right)^{\frac{k}{\varrho-1}} \tag{6}$$

Note that $\overline{z}_t^d$ depends on t via z_t^* which may fluctuate over time with economy-wide wages and durable output and prices as equation (3) shows. I defined N_t as the measure of all active firms in the economy (which is also the measure of firms active in Sector n). Let N_t^d be the measure of the subset of all firms also active in Sector d. I can now express all equilibrium quantities as averages of the "representative firm" in the economy (that has productivity $\overline{z}^n$ or $\overline{z}_t^d$ respectively) times the measure of active firms, N_t and N_t^d, respectively. These average prices, quantities and profits are

$$
\begin{aligned}
P_t^n &\equiv 1 = N^{\frac{1}{1-\sigma}} p_t^n(\overline{z}^n) = \frac{\sigma}{\sigma-1}\frac{w_t}{\overline{z}^n} N^{\frac{1}{1-\sigma}} && (7)\\
P_t^d &= (N_t^d)^{\frac{1}{1-\varrho}} p_t^d(\overline{z}^d) = \frac{\varrho}{\varrho-1}\frac{w_t}{\overline{z}_t^d}(N_t^d)^{\frac{1}{1-\varrho}} \\
&= \frac{\varrho}{\varrho-1}\frac{\sigma-1}{\sigma}\left(\frac{z_t^*}{z_L}\right)^{\frac{k+1-\varrho}{\varrho-1}}\left[\frac{k}{k+1-\varrho}N_t\right]^{\frac{\varrho-\sigma}{(\varrho-1)(\sigma-1)}} && (8)\\
y_t^n(\overline{z}^n) &= \left(\frac{\sigma-1}{\sigma}\frac{\overline{z}^n}{w_t}\right)^{\sigma} Y_t^n && (9)\\
y_t^d(\overline{z}_t^d) &= \left(\frac{\varrho-1}{\varrho}\frac{\overline{z}_t^d P_t^d}{w_t}\right)^{\varrho} Y_t^d && (10)\\
l_t^n(\overline{z}^n) = \frac{y_{it}^n}{\overline{z}^n} &= \left(\frac{\sigma-1}{\sigma}\frac{1}{w_t}\right)^{\sigma}(\overline{z}^n)^{\sigma-1} Y_t^n && (11)\\
l_t^d(\overline{z}_t^d, c_f) = \frac{y_{it}^d}{\overline{z}_t^d} + c_f &= \left(\frac{\varrho-1}{\varrho}\frac{P_t^d}{w_t}\right)^{\varrho}\left(\overline{z}_t^d\right)^{\varrho-1} Y_t^d + c_f && (12)
\end{aligned}
$$

$$
\begin{aligned}
\pi_t^n(\overline{z}^n) &= \frac{1}{\sigma}\left(\frac{\sigma-1}{\sigma}\frac{\overline{z}^n}{w_t}\right)^{\sigma-1} Y_t^n && (13)\\
\pi_t^d(\overline{z}_t^d) &= \frac{1}{\varrho}\left(\frac{\varrho-1}{\varrho}\frac{\overline{z}_t^d}{w_t}\right)^{\varrho-1}\left(P_t^d\right)^{\varrho} Y_t^d - w_t c_f && (14)
\end{aligned}
$$

The relative average price of durables deserves some more attention:

$$
\frac{p_t^d}{p_t^n} = \frac{\varrho}{\varrho-1}\frac{\sigma-1}{\sigma}\frac{\overline{z}^n}{\overline{z}_t^d}
$$

As I can see, the relative price of durables, $p_t^d(\overline{z}_t^d)/p_t^n(\overline{z}^n)$, varies over time with entry/exit and with the productivity cutoff z_t^*. The cutoff moving up leads to more efficient firms in durables on average. Equivalently, when the cutoff is high, the marginal cost in durables are lower. Because firms charge a price which is constant markup over marginal cost, and their marginal cost are lower on average, their price will be lower as well.

3.4 Firm entry and exit

For tractability reasons, firms have the possibility to be active in both durables and non-durables. One may think of a firm producing a durable good (y_{ij}^d) and also provide related services (maintainance, repair etc. of the durable good, y_{ij}^n). Firms will generate profits from both activities, selling the durable good and providing services. It is plausible to assume that these service-related revenues are not as cyclical as sales of the durable good themselves.

As in Melitz (2003), active firms die randomly at rate ζ (death shock). This is of course a strong assumption that might be related to my statements about productivity. I maintain this assumption, however, because it keeps the analysis tractable. Recent empirical research on firm entry and exit by Lee and Mukoyama (2011) have established that firm exit rates are fairly acyclical (contrary to firm entry rates which are strongly procyclical). This lends support to the assumption of an acyclical exit rate. Given this death rate, the probability of survival until period T from today is $(1-\zeta)^T$.

In every period, new firms enter if the expected net present value of profits are larger than a sunk entry cost. Sunk entry cost are denoted in units of labour c_e and receive the same wage as labour employed in production or as a fixed input. A firm makes profits every period after entry until it dies exogenously. Let v_t denote the expected pre-entry net present value (in utils – because firms are owned by households) of the profit stream. This can be written as

$$v_t = E_t\left[\sum_{\tau=1}^{\infty} \beta^{\tau} \frac{\lambda_{t+\tau}}{\lambda_t}(1-\zeta)^{\tau}\pi_{t+\tau}\right]$$

where β is the household discount factor, λ_t the Lagrange multiplier on the household budget constraint and π_t average firm profits. $\beta^{\tau}\frac{\lambda_{t+\tau}}{\lambda_t}$ is the stochastic discount factor. It denominates the period t marginal utility a household has from obtaining one unit good in period $t+\tau$. $(1-\zeta)^{\tau}$ denotes the probability of firm survival until period $t+\tau$. In any period, entry will occur until the expected profits are low enough to make the free entry condition hold.

$$v_t = c_e w_t \tag{15}$$

3.5 Households

The representative household has preferences over two goods, consumption, C_t, and services from durable goods, as well as leisure. I assume that utility from durable goods is simply a linear function in the stock of durables: ηD_t. It is assumed that durables evolve according to the following law of motion

$$D_{t+1} = (1-\delta)D_t + I_t.$$

The household offers his labour in a competitive labour market and earns real wage rate w_t. In addition to his labour income, he receives repayment and interest from bond holdings he invested in last period, $(1+r_t)B_t$ and holds shares in intermediate firms, $s_t N_t$ that entitle him to current-period profits π_t. Note that profits that go into the household budget constraint are the flow profits per share equity:

$$\pi_t = \pi_t^n + \frac{N_t^d}{N_t}\pi_t^d \tag{16}$$

The household problem is hence to maximise

$$\begin{aligned}
&\max_{C_t, D_{t+1}, L_t, s_{t+1}} U = \sum_t \beta^t \left[\frac{\left[C_t^\alpha (\eta D_t)^\gamma (1-\phi_t L_t)^\psi\right]^{1-\theta}}{1-\theta} \right] \\
&s.t. \quad (1+\tau_t^c)C_t + P_t^d (1+\tau_t^I)\left[D_{t+1} - (1-\delta)D_t\right] + v_t s_{t+1}\left(N_t + N_t^E\right) \leq \\
&\qquad w_t L_t + (v_t + \pi_t)s_t N_t + T_t
\end{aligned}$$

The household has to pay consumption and capital goods taxes, τ_t^c and τ_t^I, respectively. The government uses tax revenues to redistribute them back to hosueholds as lump-sum.

$$T_t = \tau_t^c C_t + \tau_t^i P_t^d I_t \tag{17}$$

These distortionary taxes are redistributed by the government lump-sum: T_t. How the tax rates are set will be explained momentarily.

The household is endowed with a unit measure of time and L_t is hours worked, β is his discount factor and θ, the inverse of intertemporal elasticity of substitution. ϕ_t denotes an intratemporal preference shock regulating the trade off between consumption and leisure. I assume that ϕ_t is small enough so that the optimal labor supply is still interior on the unit interval. B_{t+1} and s_{t+1} are bond and equity holdings, respectively, at the beginning of period $t+1$. v_t is the value of equity and π_t is the per-period flow profit the households receives from holding equity (dividends). It is assumed that the household portfolio is perfectly diversified across firms, so all idiosyncratic risk (death shock, productivity draw of entrants) washes out. Let λ_t be the Lagrange multiplier on on the household's budget constraint and let $X_t \equiv \left[C_t^\alpha (\eta D_t)^\gamma (1-\phi_t L_t)^\psi\right]$, then the first-order conditions are

$$\frac{\alpha}{C_t} X_t^{1-\theta} = \lambda_t (1+\tau_t^c) \tag{18}$$

$$\lambda_t P_t^d (1+\tau_t^I) = \beta\lambda_{t+1}(1+\tau_{t+1}^I)P_{t+1}^d(1-\delta) + \beta X_{t+1}^{1-\theta}\frac{\gamma}{D_{t+1}} \tag{19}$$

$$X_t^{1-\theta}\frac{\psi\phi_t}{(1-\phi_t L_t)} = \lambda_t w_t \tag{20}$$

$$\lambda_t v_t (N_t + N_t^E) = \beta\lambda_{t+1}(v_{t+1} + \pi_{t+1})N_{t+1}$$

$$\lambda_t v_t = \beta(1-\zeta)\lambda_{t+1}(v_{t+1} + \pi_{t+1}) \tag{21}$$

Keep in mind that the timing assumptions about firm entry and death imply that

$$N_{t+1} = (1 - \zeta)(N_t + N_t^E). \tag{22}$$

The death shock hits at the end of period t; it hits all incumbent firms, N_t, and all firms that just entered in t and planned to take up production in period $t+1$.

3.6 Equilibrium

Labour market Aggregate labour demand is key as shocks to aggregate demand drive labour demand which in turn drives the wage and therefore fixed cost. Aggregate labour demand is

$$L_t = N_t l(\bar{z}^n) + N_t^d l(\bar{z}_t^d) + N_t^E c_e \tag{23}$$

Equation (23) denotes aggregate labour demand while equation (20) determines aggregate labour supply. Both taken together determine equilibrium.

Goods market There are two goods, durables and non-durables that are each produced by the final goods producer in each sector and purchased by households:

$$Y_t^n = C_t \tag{24}$$

$$Y_t^d = I_t = D_{t+1} - (1 - \delta)D_t \tag{25}$$

Resource Constraint This is basically the budget constraint reformulated

$$w_t L_t + N_t \pi_t + N_t v_t = C_t + P_t^d \left[D_{t+1} - (1 - \delta)D_t\right] + (N_t + N_t^E)v_t \tag{26}$$

General equilibrium The equilibrium consists of a set of endogenous variables

$$z_t^*, \bar{z}_t^d, P_t^d, Y_t^n, Y_t^d, y_t^n, y_t^d, l_t^n, l_t^d, \pi_t^n, \pi_t^d, \pi_t, N_t, N_t^E, N_t^d, v_t, C_t, I_t, \lambda_t, L_t, w_t$$

that satisfies firm and household optimality as well as feasibility as prescribed by equations (3), (5)-(26).

Determinacy The model may have multiple equilibria. This feature arises from the endogenous selection of firms into durable goods production. To illustrate the possibility of multiplicity, consider the following scenario near a deterministic steady state: In the absence of shocks, households think about increasing their demand for durables today, I_t increases, and reducing it tomorrow, I_{t+1} falls. If the equilibrium was unique, such a strategy would lead to an increase in marginal utility of consumption today (λ_t) and decrease of marginal utility from both consumption and durables tomorrow ($\lambda_{t+1}, u'(D_{t+1})$) and equation (19) would not hold. In particular, increasing demand for durables would increase the price of them today (higher P_t^d) and lower demand tomorrow would decrease the relative price of durables (lower P_{t+1}^d), thus violating equation (19) even more. In the present context, the scenario just described is feasible without violating any equilibrium conditions. Additional demand for durables today triggers firm entry. This in turn increases labour demand and hence the wage, which is the main component of the productivity cutoff (3). If the cutoff increases, average productivity increases and the relative price of durables *falls* thus justifying the initial beliefs of households. The key feature of this model is that an *increase* in demand for durables can lead to a *lower* relative price of durables.

This little example shows how beliefs can become self-fulfilling. This is an interesting feature of the model as it allows for endogenous fluctuations. Two factors can mitigate this decrease in the relative price and keep the equilibrium in the model economy determinate: a low intertemporal elasticity of substitution (high θ) and taxes on investment goods that increase when demand is high (high τ_t^I).[39] The multiplicity feature of this model context is subject of ongoing research. In the present paper, I focus on a unique equilibrium in the model. θ is calibrated to economically plausible values consistent with other research. The taxes are allowed to be a function of economic activity:

$$\tau_t^c = \overline{\tau}^c + x_c^c C_t + x_c^L L_t$$
$$\tau_t^i = \overline{\tau}^i + x_i^i I_t + x_i^L L_t$$

Tax rates in the current period, τ_t^c and τ_t^i are a function of the long-run average tax rate, $\overline{\tau}^c$ and $\overline{\tau}^I$, and the levels of consumption and investment. We can think of the fact that taxes are dependent on current economic activity as as implicit policy maker that attempts to design tax policy according to economic conditions. If $x_\bullet^\bullet > 0$ this corresponds to countercyclical fiscal policy. This "countercyclical fiscal policy" does not seem implausible. Relaxing this assumption and analysing endogenous fluctuations in the context of this model is subject of future research.

Shock and calibration At present, the model is driven by one shock in the household sector that evolves over time as follows (in logs)

$$\phi_t = (1 - \rho_\phi)\overline{\phi} + \rho_\phi \phi_{t-1} + \varepsilon_t^\phi$$

[39]This approach is chosen in Christiano and Harrison (1999).

where $\overline{\phi}$ is the steady state value, ρ_ϕ the autocorrelation and the disturbances is independent and distributed normally as

$$\varepsilon_t^\phi \sim \mathcal{N}(0, \sigma_\phi).$$

The shock to intratemporal preferences is primarily meant to serve as a stand-in for a disturbance that will alter aggregate demand for consumption and durables goods. The model could be extended to feature a richer set of shocks, but the key exercise is to study the dynamics of the model economy when demand rises and the cost of fixed inputs change.

Table 8: Calibration

Parameter	Symbol	Value
Pareto Distribution: Shape	k	4.5
Pareto Distribution: Lower bound	z_L	1
Rate of death shock	ζ	0.07
EOS non-durables	σ	5.4
EOS durables	ϱ	3.5
Sunk entry cost	c_e	5
Fixed Cost in Durables	c_f	0.1
Deprecitation rate durables	δ	0.085
Discount Factor	β	0.9925
Inv. intertemporal EOS	θ	1.5
Utility weight non-durables	α	0.66
Utility weight durables	γ	$1-\alpha$
Utility weight leisure	ψ	0.7
Mean consumption tax rate	$\overline{\tau}^c$	0.1
Mean investment tax rate	$\overline{\tau}^i$	0.2
Inv. Tax dependence on I	x_i^i	2.5
Inv. Tax dependence on L	x_i^L	0.5
Mean demand shock	$\overline{\phi}$	1
Autocorrelation demand shock	ρ_ϕ	0.8
Std. Dev. demand shock	σ_ϕ	1

Table 8 displays the parameters chosen for calibration. The productivity distribution is parametrised as a Pareto with lower bound $z_L = 1$ and shape parameter k. The shape parameter is the smallest admissible value that satisfies the condition $k > \sigma - 1$ and $k > \varrho - 1$. Recall that these conditions are necessary if we want to restrict attention to positive equilibrium quantities and prices. In accordance with the literature on mark-ups, σ and ϱ are chosen to equal 5.4 and 3.5 respectively which gives the smallest possible value for k as 4.5. The rate of death shock, ζ, is chosen to match the exit rate in my sample. The fixed input factor c_f is chosen to match the observed steady state difference in returns to scale in the durable and non-durable goods sector. The depreciation rate in consumer durables, δ, is set to 0.085 to match an annual depreciation rate of about 30% as common for consumer durables. The discount rate $\beta = 0.9925$ reflects an annual real interest rate of about 3%. The intertemporal elasticity of substitution $\theta = 1.5$ is chosen to accord with empirical studies. The utility weight on consumption, α, is set equal to 0.66 in order to match expenditure shares for consumption goods.

3.7 Dynamics of the economy

How does the economy respond to a shock to ϕ? This shock originally shifts the labour supply schedule and also change the consumption plan. In that way, we can think about it as a shock that alters aggregate demand. I shall first describe the initial adjustment on impact and the dynamic response. The outward shift in labour supply increases employment while leaving the wage initially unaffected. This is rather unusual and it is a consequence of firm technology. It is linear homogeneous in labour, so that the marginal product of labour is independent of the level of labour. The increased employment leads to higher labour income which immediately raises demand for consumption and investment goods. With a constant wage this raises profits. In light of higher profits, new firms enter up to the point that the free entry condition equation (15) holds. The new equilibrium right after the impact of the shock involves higher employment, output, consumption, investment and more entrants (that will not be active until the next period).

In the periods after the shock, new firm entry continues, but it gradually converges back to its steady state level. This is illustrated in panel (3,2) of Figure 6. The additional entry leads to a hump-shaped rise in the mass of incumbent firms panel (3,1) which in turn increases labour demand in a similar fashion – see panel (2,1). Because aggregate labour demand increases, so do real wages, displayed in panel (2,2).[40] Real wages are a key factor in the productivity cutoff. As the cutoff rises, see panel (1,1), the productivity distribution in durables becomes more compressed, thus leading to negative co-movement between output and productivity dispersion. This is the key result of the theoretical part of the model: It is possible to reconcile a boom with a more compressed productivity dispersion. This happens although the model in principle does allow for cleansing. A second consequence of a rising productivity cutoff is that the average productivity in durables increases. This lowers the average marginal cost and thus the average relative price of durables which is displayed in panel (1,2). This feature is a nice complement to the literature on investment-specific technological change which has to rely on exogenous technology shocks in the durable goods sector. In this model, the relative price of

[40] Note that wages also increase because of additional entry into the economy and a higher mass of firms paying the fixed cost to produce in durables. This is merely reinforcing the effect of additional labour demand in production.

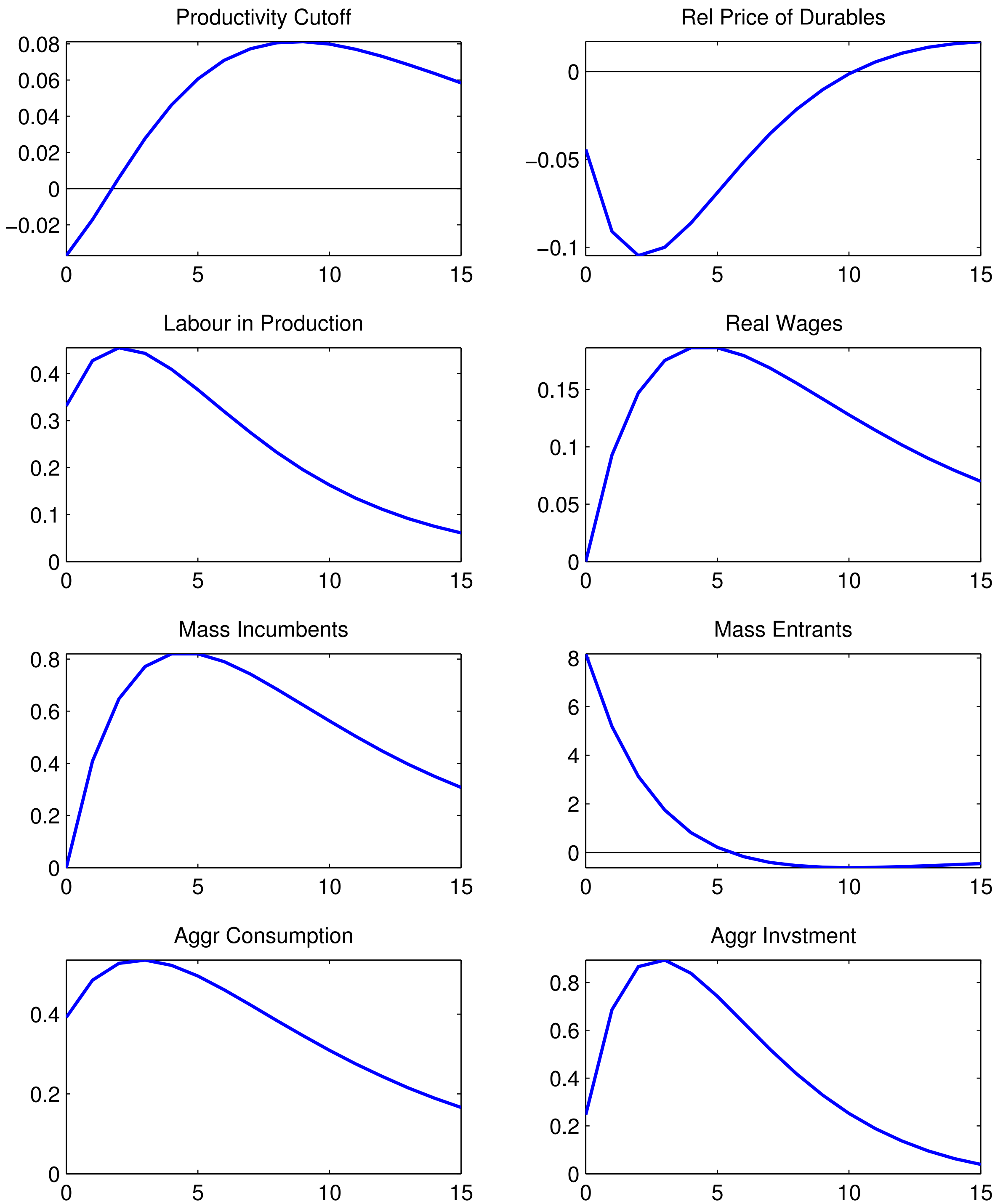

Figure 6: Impulse Response Function of an aggregate demand shock to ϕ

durables fluctuates endogenously due to the selection along a rising productivity cutoff in a boom. Lastly, both consumption and durables purchases increase, see panels (4,1) and (4,2). Households dispose over a higher income, so they increase their demand for goods overall. As panel (4,2) illustrates, this rise is stronger in durables purchases which is partly due to the relative price of durables declining.

4 Conclusion

This paper established the dynamics of the empirical productivity distribution over the business cycle. Among U.S. manufacturing plants, this dispersion is higher in a recession than in a boom. These cyclical dynamics are predominantly driven by changes in the lower quantiles. This evidence can be interpreted as a changing truncation at the bottom end of the productivity distribution in durables. Lastly, dispersion appears to be more negatively correlated with the business cycle in durable goods industries relative to non-durable goods industries.

This countercyclical productivity dispersion is at odds with conventional cleansing models of the business cycle which posit a procyclical productivity dispersion. In order to reconcile these models with the empirical findings, I build a business cycle model along the lines of Ghironi and Melitz (2005). In my model, a shock that originates in the household sector and changes aggregate demand is consistent with a countercyclical productivity dispersion. In addition to that, this shock is also consistent with the typical macroeconomic business cycle acts such as procyclical consumption, investment, wages and employment.

I will direct future research at introducing more shocks into the model. It is plausible to assume that some shocks deliver the empirically observed outcome and others do not. Which are these and what is their distinct criterion? A second possible extension is to focus on a micro-founded theory of investment-specific fluctuations. The endogenous selection of firms into durables on a productivity threshold is an interesting mechanism that can contribute to the research programme on investment-specific technical change. Furthermore, this avenue will also open the possibility to look into endogenous fluctuations that arise from indeterminacy.

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Appendix

A Census manufacturing data

A.1 General description

The data used in this project are compiled by the U.S. Census Bureau and comprise the Census of Manufactures (CMF), the Annual Survey of Manufactures (ASM) and the Plant Capacity Utilization Survey (PCU). Additional data come from the NBER-CES productivity database, the Federal Reserve Board of Governors (data on capacity utilization), the Bureau of Economic Analysis (BEA; data on capital stocks and investment prices), the Bureau of Labor Statistics (BLS; data on depreciation rates and inventory price deflators). The Compustat-SSEL bridge (CPST-SSEL) is used to determine which establishments are publicly traded (are covered in Compustat).

The main data sources are the CMF/ASM. They are both mail-back surveys and cover the U.S. manufacturing sector (NAICS 31-33) on the establishment level where establishment is defined as any distinct unit of a manufacturing firm where the predominant activity is production. Purely administrative establishments are hence excluded. Each establishment carries the Permanent Plant Number (`PPN`), a unique establishment identifier that does not change in case of ownership change or temporary plant shutdown. If an establishment dies permanently, the `PPN` is not reassigned to a new-born establishment. Since 2002, the `PPN` is superseded by the Survey Unit ID (`SURVU_ID`). This more recent identifier was carefully mapped to the `PPN` using `LEGPPN` and `LBDNUM` or assigned a new `PPN` if an establishment was born after 2002. Establishments that belong to the same legal firm carry the same firm identifier `FIRMID`. Firms are called multi-unit firms (MUF) if they operate more than one establishment, single-unit firm (SUF) if they operate merely one.

The Census of Manufactures is conducted at quinquennial frequency (years ending in 2 and 7) and covers all existing 300-350k establishments in the manufacturing sector. The ASM is conducted in non-Census years for about 50-60k establishments taken from the "mail stratum" of the manufacturing sector. The "non-mail stratum" generally consists of small establishments that together make up a very small fraction of activity; their chance to be selected in to the ASM panel is zero. I drop all observations from the non-mail stratum (denotedby `ET` $= 0$) because this is the only way to obtain a consistent panel over time where the number of (weighted) observations is not driven by the sampling constraints of Census. Of the mail stratum, the ASM covers all "large" establishments with certainty and a selection of "small" establishments. The criteria for an establishment to qualify as large are cutoffs changed over time. In principle, these are cutoffs in terms of asset size, employment or industry share and. For all establishments in the ASM, Census provides frequency weights which are the inverse of the sampling probability and can be used to replicate the underlying population where the sampled small establishments are representative of the establishments not sampled in the ASM. Every five years (years ending in 4 and 9) Census updates its small establishment sample according to the preceding Census to accurately reflect the underlying age and size population. Census attempts to sample the same small establishments in consecutive years until the next sample update.

The data carry a wide array of variables only some of which are of interest for this project. These are data on sales, inventories, employment and hours, capital stocks and investment, intermediates and energy. The following sections describe how observed variables are used to construct measures needed for the estimation.

A.2 Measurement of real production

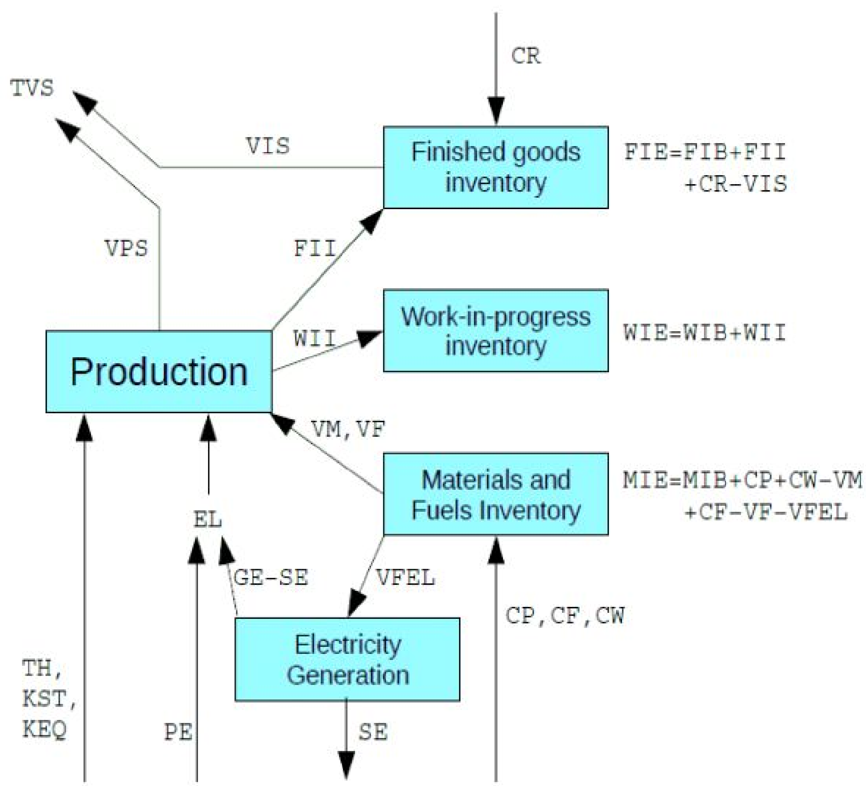

Figure 7: ASM flowchart

Note: Flow of inputs, outputs and inventories as they are measured in the ASM. All variables are nominal except hours worked (TH) and the real value of the capital stocks of structures (KST) and equipment (KEQ).

The object of interest is a real measure of goods produced (Q). It consists of goods that are produced and sold in the same year (PS) and produced goods that are stored in either of two inventories: finished-goods inventory investment ($\texttt{FII}^{\texttt{real}}$) and work-in-progress inventory investment ($\mathtt{WII}^{\mathtt{real}}$).

$$\mathtt{Q} = \mathtt{PS} + \mathtt{FII}^{\mathtt{real}} + \mathtt{WII}^{\mathtt{real}}$$

The first term (PS) comprises receipts from goods produced and sold in the same period. Census collects information about some components of this term (such as product value of shipments, receipts for contract work), but their quality is not consistently reliable throughout the entire sample. Fortunately, total value of shipments (TVS) is considered by Census to be of superior quality. We can use this variable to infer PS as shown in Figure 7.

$$\mathtt{PS} = \frac{\mathtt{VPS}}{\mathtt{PISHIP}} = \frac{\mathtt{TVS} - \mathtt{VIS}}{\mathtt{PISHIP}}$$

where VPS is the nominal value of product shipments, PISHIP is a price deflator on the 4-digit (SIC) industry level from the NBER-CES Manufacturing Productivity Database and VIS is value of inventory sales. The last variable is not directly observed but will conveniently cancel out as explained below.

The second term, $\mathtt{FII}^{\mathtt{real}}$, can be constructed from nominal finished goods inventory investment which in turn can be constructed from the accounting identity:
$\mathtt{FIE} = \mathtt{FIB} + \mathtt{FII} + (\mathtt{CR} - \mathtt{VIS})\frac{\mathtt{PIFI}}{\mathtt{PISHIP}}$. This expression contrasts with previous work and deserves more explanation. FIB and FIE denote the nominal value of finished goods inventory at the beginning and end of the period. FII is the value of produced goods that go into finished-goods inventories rather than being sold on the market in the same period. Note that FII is non-negative, because finished goods never flow back from the inventory to production. The last inflow into the finished goods inventory are resales (CR), finished goods purchased from other establishments that are resold without further changes or additions. Inventories that are sold in the current period are denoted by VIS. We do not observe VIS directly (though this shall not be a problem); we only know the portion of VIS that are resales (VR).[41]

Resales (CR) and inventory sales (VIS) are traded in the goods market at the market price (PISHIP), while inventory stocks (FIB and FIE) and inventory investment (FII) are valued with a price index for finished-goods inventories (PIFI). This is why the former three variables have to be adjusted for that. Empirically, PIFI is much more volatile than PISHIP and also exhibits a slightly different trend growth rate[42], so this difference might matter when one computes finished inventory investment:

[41] Note that resales (CR and VR) are already finished goods, so they will not enter the materials inventory and eventually put through the production process, as was assumed by other researchers. In fact, counting them as material inputs would lead to biased results of production elasticities and productivity (more details below).

[42] This is because inventories are typically older goods of lower quality than those produced in the current period. Quality-adjusted price indices for inventories exhibit hence a higher growth rate than shipment price indices of the same product.

$$\mathtt{FII}^{\mathtt{real}} = \frac{\mathtt{FIE} - \mathtt{FIB}}{\mathtt{PIFI}} - \frac{\mathtt{CR} - \mathtt{VIS}}{\mathtt{PISHIP}}$$

I assume that both FIB and FIE are nominal stocks of inventories that are valued with the inventory price deflator from period t, which is supported by the fact that in many cases $\mathtt{FIE}_{\mathtt{t-1}} \neq \mathtt{FIB}_{\mathtt{t}}$. Census sends establishments the ASM/CMF forms at the beginning of the period with end-of-year inventory stock pre-printed in the FIB cell. Establishments are allowed, however, to make changes; this is how last year's end-of-year inventories may differ from this year's beginning-of-year inventories.

The third term, $\mathtt{WII}^{\mathtt{real}}$, can be constructed from the accounting identity: $\mathtt{WIE} = \mathtt{WIB} + \mathtt{WII}$ where, contrary to above, $\mathtt{WII} \gtreqless 0$. No work-in-progress inventories are traded in markets, so terms merely have to be deflated by the price index for work-in-progress inventories (PIWI):

$$\mathtt{WII}^{\mathtt{real}} = \frac{\mathtt{WIE} - \mathtt{WIB}}{\mathtt{PIWI}}$$

Putting all three terms together yields:

$$\begin{aligned} \mathtt{Q} &= \mathtt{PS} + \mathtt{FII}^{\mathtt{real}} + \mathtt{WII}^{\mathtt{real}} \\ &= \frac{\mathtt{TVS} - \mathtt{VIS}}{\mathtt{PISHIP}} + \frac{\mathtt{FIE} - \mathtt{FIB}}{\mathtt{PIFI}} - \frac{\mathtt{CR} - \mathtt{VIS}}{\mathtt{PISHIP}} + \frac{\mathtt{WIE} - \mathtt{WIB}}{\mathtt{PIWI}} \\ \mathtt{Q} &= \frac{\mathtt{TVS} - \mathtt{CR}}{\mathtt{PISHIP}} + \frac{\mathtt{FIE} - \mathtt{FIB}}{\mathtt{PIFI}} + \frac{\mathtt{WIE} - \mathtt{WIB}}{\mathtt{PIWI}} \qquad (27) \end{aligned}$$

All of these variables are directly observed in the ASM/CMF except for the price deflators, which are obviously not available on the establishment level. I approximate PISHIP by the 4 digit-level industry price index for shipments from the NBER-CES Manufacturing Productivity Database; PIFI and PIWI are ideally industry-level price index for inventory investment (finished goods and work-in-progress goods respectively). BEA does produce inventory price deflators adjusted for quality on the industry level and separately for both finished and unfinished goods, but unfortunately, these are not publicly available, only to BEA sworn status researchers.[43] BLS published an inventory price deflator on the industry level, but this one contains a mix of finished goods, unfinished goods and materials inventories, so it merely looks like a crude measure. For that reason, I have to fall back to use shipment price deflators instead of inventory price deflators. Future researchers that have access to industry-wide deflators for inventories by type can easily combine them with the existing data and produce more accurate measures of output. While the present procedure is as good as one can possibly do to correct for prices, this can lead to inefficient estimates and possibly to further problems estimating total factor productivity, which will be discussed below.[44]

[43] Census researchers that have special sworn status are not entitled to obtain the data either.

[44] At this point, I am following the large productivity literature and estimate revenue factor productivity (TFPR

The construction of the ouptut variable improves on previous research in two ways: First, some work has ignored the role of inventories when constructing output variables (exceptions are Hyowook Chiang's measure or Petrin, Reiter and White (2011)). This seems problematic since inventory investment is known to fluctuate a lot; for example, it has a much higher volatility than investment in new capital (see Christiano (1988)). Second, in contrast to previous researchers, I classify resales (`CR`) as finished goods rather than a materials. Classifying cost of resales as a material input used in production and not correcting the output measure by the value of resales (`VR`) seems misplaced: By definition, resales are products that are bought and then resold without any change to the product. They are therefore not going through the production process and provide no information about the firm's productivity as a producer of goods. Even worse, a researcher running a production function regression to study productivity will obtain biased estimates of production elasticities and as a consequence also biased estimates of productivity. Counting `CR` as material input and not correcting the output measure will bias the coefficient estimate of materials towards 1 (i.e upwards) and it will also bias all other coefficient estimates (downward). Even small values of resales (`CR` is on average 5% of overall materials purchases) bias the estimates significantly.[45]

A.3 Measurement of labor input

The ideal measure is hours worked of all workers. The ASM/CMF only carries information on plant hours worked (`PH`), which covers only production workers, so hours of non-production workers have to be imputed. In addition to the number of total employees (`TE`), production workers (`PW`) and production worker hours (`PH`), the ASM/CMF carries information about wage payments for all employees (`SW`) and production workers (`WW`), which contain some information about the hours worked if one has an idea about the level of wages. Wages and salaries can be exploited to construct a more accurate measure of total hours worked. Let `WP` and `WNP` denote the average wages for production and non-production workers, respectively. Then, total hours (`TH`) can be expressed as the sum of production worker hours (`PH`) and non-production worker hours (`NPH`):

$$\mathtt{TH} = \mathtt{PH} + \mathtt{NPH} = \mathtt{PH} + \frac{\mathtt{SW} - \mathtt{WW}}{\mathtt{WNP}}.$$

Wages for production workers can be computed as $\mathtt{WP} = \frac{\mathtt{WW}}{\mathtt{PH}}$. Unfortunately, wages of non-production workers are not observed in the ASM/CMF. I assume that the wages for non-production workers (`WNP`) are 150% of those for production workers (`WP`): $\mathtt{WNP} = 1.5 \times \frac{\mathtt{WW}}{\mathtt{PH}}$.[46]

in Foster, Haltiwanger and Syverson (2008) or Hsieh and Klenow (2009)).

[45] As a check on the strength of this bias I simulated 1000 observations of the following technology: $Y = K^a M^b$ with $a = 0.1$ and $b = 0.45$. Estimating a and b using $Y = Y + CR$ and $M = M + CR$ instead yields the following estimates $\hat{a} \approx 0.05$ and $\hat{b} \approx 0.52$ even when $\mathtt{CR} = 0.05M$. This bias obviously becomes stronger the larger `CR`.

[46] A very proper way would be to utilise external information from the Current Population Survey to construct

Total hours under this assumption can be calculated as:

$$\begin{aligned} \mathtt{TH} &= \mathtt{PH} + \mathtt{NPH} \\ &= \mathtt{PH} + \frac{\mathtt{SW} - \mathtt{WW}}{\mathtt{WNP}} \\ &= \mathtt{PH} + \frac{\mathtt{SW} - \mathtt{WW}}{1.5 \times \mathtt{WP}} \\ \mathtt{TH} &= \mathtt{PH}\, \frac{\mathtt{SW} + 0.5 \times \mathtt{WW}}{1.5 \times \mathtt{WW}} \end{aligned} \tag{28}$$

Total hours worked can be constructed in this way for about 97.6% of all observations. The remaining observations do not have information on either of PH, SW or WW. In that case, I set $\mathtt{TH} = 2 \times \mathtt{TE}$ (50 weeks of 40 hrs/week each).

There is not a major improvement in the construction of the hours worked variable over previous research. If I do get the CPS data in then the imputation of non-production worker hours would be a substantial improvement.

A.4 Measurement of capital input

Capital input (or capital services) in production, $\tilde{K}_t$, are determined by both the existing productive capital *stock* available to the firm, K_t, and the *utilisation* at which this stock is run, u_t. The latter is a percentage, so the object of interest, capital services are defined as the product of stock and utilisation:

$$\tilde{K}_t \equiv u_t K_t. \tag{29}$$

First, I shall describe how I measure the capital stock that is available to the firm for production, then the utilisation of the capital stock.

---

annual industry-region-specific average wages for both production workers and non-production workers, which gives an industry-region-year-specific ratio of the two average wages: $\mathtt{a} = \frac{\mathtt{WNP}}{\mathtt{WP}}$. Then, total hours can be computed on the establishment level as:

$$\mathtt{TH} = \mathtt{PH} + \frac{\mathtt{SW} - \mathtt{WW}}{\mathtt{WNP}} = \mathtt{PH} + \frac{\mathtt{SW} - \mathtt{WW}}{\mathtt{a} \times \mathtt{WP}} = \mathtt{PH}\, \frac{\mathtt{SW} + (\mathtt{a} - 1) \times \mathtt{WW}}{\mathtt{a} \times \mathtt{WW}}.$$

ALTERNATIVE:

One could get data on hours worked per employee in both production and non-production: $\mathtt{HRS}_{\mathtt{PW}}$ and $\mathtt{HRS}_{\mathtt{NPW}}$. These data should be available on an industry-region level in the CPS. Then, total hours can be computed as $\mathtt{TH} = \mathtt{HRS}_{\mathtt{PW}} \times \mathtt{PW} + \mathtt{HRS}_{\mathtt{NPW}} \times \mathtt{NPW}$ The disadvantage of this approach is that it implicitly assumes that all workers within an industry work the same amount of hours. Overtime work is not accounted for. As outlined above, wage payments on the other hand, do contain information about establishment-level overtime (and possibly part-time). Therefore, this approach based on industry-wide hours worked per employee would forgo all the information about hours worked contained in wage payments.

A.4.1 Capital stocks

The capital stock is – ideally – the replacement value of fixed assets in constant dollars. In the absence of frictions, this is the value another firm would be willing to pay to acquire and operate this capital stock itself. In this sense, the replacement value should be an accurate measure of the productivity of the capital stock. Below, I will describe how I infer the closest approximation possible to this constant-dollars replacement value.

The ASM/CMF contains the following information related to capital:

- beginning-of-year and end-of-year total assets (`TAB` and `TAE`)
  - annually 1972-1988; in those years total assets are also separated into buildings (structures) and machinery (equipment): `BAB`, `BAE`, `MAB` and `MAE`
  - quinquennially 1992-2007,
- nominal investment expenditures for buildings (`NB`) and machinery (`NM`) for all years; in 1977-1996 investment expenditures are separated into investment in new and used capital: `NB`, `UB`, `NM` and `UM`,
- nominal building and machinery retirements (1977-1988, 1992): `BRT` and `MRT`,
- nominal building and machinery depreciation (1977-1988, 1992): `BD` and `MD`,
- nominal cost of rented building and machinery (1977-1988, 1992): `BR` and `MR`.

Investment, retirement and depreciation of assets are measured in period-t dollars. Assets stocks (`TAB`, `TAE`, `BAB`, `BAE`, `MAB`, `MAE`), however, are somehow resembling book values rather than resale values. To obtain constant-dollar market values I perform three steps:

1. Transformation of reported values into book values,
2. Transformation of book values into period-t market values,
3. Transformation of period-t market values into constant-dollar values.

Transformation into book values The questionnaire of the ASM/CMF asks to list as asset stock values "the original cost of today's assets when they were purchased" in the past. It is not clear from the information given in the documentation whether or not this value takes (physical[47]) depreciation into account or not. If respondents answered the question literally, then it does not include depreciation and is not exactly a book value. If it does, then the

[47] It is important to consider physical depreciation rather than depreciation on the books. The latter is an accounting measure and does not necessarily reflect the accurate loss of productive capability of structures or equipment. An establishment might use a machine in production that is already entirely written off on the books.

reported data really are book values. I tried imputing the capital stock both ways. When I aggregate my capital stock measure and compare it to BEA's industry-wide capital stock, the level of my capital stock is slightly too high while the trend compares well to the BEA capital stock, so my level is off by a constant factor. This level gap is much smaller when I correct the initial values for depreciation.[48] This suggests, that some respondents took the question literally and reported as asset values the initial expenditures unaccounted for by depreciation, others did take depreciation into account. Multiplying the reported capital stock values by $(1-\delta)$ transforms the observations into book values that will yield an aggregate time series that precisely matches the trend growth and roughly matches the absolute level.

Transformation into market values Transforming book values into market values requires (a) knowledge about the vintage structure of each establishment and (b) knowledge about the productivity of each vintage. This cannot be determined on the establishment level because we just know the dollar amount of investment but hardly the quality of the purchased capital.[49] The quality of the vintage, however, is crucial to determine the replacement value.

Due to the paucity of information on the establishment level, I turn to industry-level capital stock data published by the Bureau of Economic Analysis (BEA).[50] BEA publishes historical-cost, current-cost and real-cost estimates of capital stocks of 3-digit NAICS (2-digit SIC) industries that can help turn the ASM book values into real market values. For a single asset type, these end-of-year estimates[51] are defined as follows:

$$
\begin{aligned}
HC_t &= \sum_{\tau=0} \left(1-\frac{\delta}{2}\right)(1-\delta)^{\tau} I_{t-\tau} \\
CC_t &= P_t \sum_{\tau=0} \left(1-\frac{\delta}{2}\right)(1-\delta)^{\tau} \frac{I_{t-\tau}}{P_{t-\tau}} \\
RC_t &= \sum_{\tau=0} \left(1-\frac{\delta}{2}\right)(1-\delta)^{\tau} \frac{I_{t-\tau}}{P_{t-\tau}}
\end{aligned}
$$

where τ is the vintage (purchased τ periods before period t), δ is the depreciation rate, and I_t are nominal investment expenditures in period t. The term $\left(1-\frac{\delta}{2}\right)$ appears because BEA assumes that new capital is put into place in the middle of the period. Note how the historical-

[48] Multiplying the reported initial measure by $(1-\delta)$ implicitly assumes that capital stocks are one year old. An alternative, more refined method would be to construct the average age, $\tilde{T}$, of an establishment's capital stock from past investment expenditures and multiply the reported capital stock value by $(1-\delta)^{\tilde{T}}$. The former way (assuming average age of one year) yields aggregate capital stocks that are slightly too high, an approximation of the latter way (assuming average age as reported by BEA, which is about 22 years for structures and 6 years for equipment capital) yields aggregate capital stocks that are distinctly too low.

[49] As mentioned above, investment in new and used capital goods are reported in the data only for a subsample.

[50] Tables 3.1E, 3.1S, 3.2E, 3.2S, 3.3E and 3.3S of BEA's Fixed Asset Tables; downloaded from http://www.bea.gov/national/FA2004/SelectTable.asp.

[51] Because I use beginning-of-year capital stocks BEA's data are rolled forward one year.

cost capital stock is the industry analogue to the establishment book value. The current-dollar value, in contrast, is the nominal value of the capital stock in year-t dollars where expenditures for every vintage have been deflated by the corresponding period price index and then reinflated by the current-period price index (hence the name). In this way, the CC_t measure denotes the value of the capital stock as if it had been purchased at the end of the previous period. I assume that all establishments within an industry have a similar ratio of current-dollar market values to book values. Then I can use the ratio of $\frac{CC_t}{HC_t}$ to determine the period-t market value of an establishment's capital stock.

Transformation into constant dollars This is then easily expressed in constant dollars by deflating the resulting measure by an investment price deflator.[52] Investment price deflators are published by the Bureau of Labor Statistics (BLS) and the Bureau of Economic Analysis (BEA) on the 3-digit NAICS industry level and on the 4-digit industry level as underlying table to the NBER Manufacturing Database.[53] I choose the BEA deflators because they were revised recently (in 2009), which matters a lot for capital goods (esp. equipment).[54] All three transformation steps (reported to book value, book value to market value and period-t to constant-dollars transformation) combined give us the replacement value of an establishment's capital stock in constant dollars as:

$$K_t^{st} = \mathtt{BAB}_t(1-\delta^{st})\frac{CC_t^{st}}{HC_t^{st}}\frac{1}{P_t^{st}} \tag{30}$$

and analoguously for equipment capital. This procedure is accurate if all establishments in an industry exhibit the same profile across asset types and have the same vintage structure over time. This is obviously a strong assumption which is likely to be violated and lead to establishment-level measurement error.

For the years 1972-1988, I observe the capital stock annually and could compute the capital stocks in the above-mentioned way. Alternatively, I could iterate the capital stock every period

[52]Note that this is an investment price deflator rather than a capital price deflator because the capital stock is now expressed as if it had been an investment at the end of last period.

[53]The investment price deflator could also be obtained from BEA by dividing CC/RC, but BEA warns researchers that the latter measure is not very reliable for years reaching far back. For that reason, I make use of the price indices published by BLS.

[54]I also tried the NBER and BLS deflators; the former do almost as good a job as the BEA deflators when one aggregates the establishment-level data and compares them to publicly available industry aggregates of capital stocks by type. BLS deflators cannot generate aggregates that resemble publicly available aggregates as well, which is mostly due to their price indices being only revised for the last 20 years. Once NBER deflators are updated in the future, they might be a superior measure as they go down to the 4-digit NAICS industry level.

using the perpetual inventory method:

$$K_{t+1}^{st} = (1 - \delta_t^{st})K_t^{st} + I_t^{st} \tag{31}$$

where K_t^{st} is the stock of structure capital observed at the beginning of the period, $I_t^{st} = \frac{\mathtt{NB}_t}{P_t^{st}}$ is real structure investment (nominal new and used[55] investment expenditures divided by an investment price index) and δ_t is a depreciation rate, published by BLS on the 3-digit NAICS industry level in period t. The former way of directly deflating the capital stock every period has the advantage of following the establishment-level information very closely. The latter perpetual inventory method shows exactly how the existing capital stock came about and follows a common procedure (see for example Becker et al. (2004)). I tried both alternatives and for equipment capital there is hardly any difference which supports the consistency of our above deflation technique. The procedure to directly deflate the capital stock every period underestimates structure capital compared to aggregate data on structures from BEA. Over the course of 20 years (1972-1992) the aggregate structure capital stock grows only at an annual rate of 0.15% which translates into a share of structures in total assets of 33.5% (while it should be about 45%). This implies that my interpretation of the structures measure in the CMF/ASM is flawed, which casts some doubt on the initialisation procedure as shown in equation. Therefore, I am sceptical of resetting the capital stock back to the value implied by equation (30) every time I observe it for continuing establishments. The perpetual inventory method, in contrast, does a good job at generating data that – aggregated to the industry level – resemble outside sources in terms of long-run growth. For this reason, I choose the perpetual inventory method and use the asset stock data observed every year to merely adjust the level of the implied total capital stock (keeping the asset split implied by the perpetual inventory method). I only use equation (30) to impute structures and equipment stocks directly when I observe an establishment for the first time.

From 1988 on, asset stock values, retirement and depreciation data are no longer observed. So I have to iterate and face the question of resetting or continuing the perpetual inventory method every five years. For the same reason as above, I proceed with the perpetual inventory method and merely adjust the implied book value of the imputed capital stocks by the book value (accounted for by depreciation) that is observed in the Census years. This procedure can be applied to both buildings (structures) and machinery (equipment) separately as the ASM/CMF contains investment data about both types.

[55] Census collected investment expenditures separately for new and used investment 1977-1996; in those years I sum the two groups and that in others years reported investment comprises both expenditures for new and used investment.

Improvements in the measurement of the capital stock The capital stock measures differ from previous work about imputing capital stocks in the ASM. This is different because previous work omitted the second deflation step (period-t market values to constant-dollars market values) and because deflators used in that work have been revised repeatedly. As a consequence, the old capital stock measures were too small at the beginning and too large at the end of the sample (as Figure 8 shows). Because the second deflation was omitted, the capital stock is a nominal value rather than a real one. It is not surprising in this light that the capital stock in the old sample is growing at an annual rate of 4.9% for structures (!) and 5.6% for equipment respectively. This barely squares with industry-wide aggregates where the capital stock grows at 1.1% and 2.6% (structures and equipment resp.). My measures end up at 1.2% and 2.7% which looks pretty close to the data published by BEA. This will have some important implication for researchers that used/are using his data. In my assessment of long- and short-run productivity the nominal trend picks up a lot of the upward trend in production. Second, because the investment price deflators are industry-year-specific, this essentially introduces industry-year dummies into a regression analysis. The former will put an upward bias to the coefficient on capital while the former will pick up industry-year-specifics that are not necessarily rooted in the capital stock.

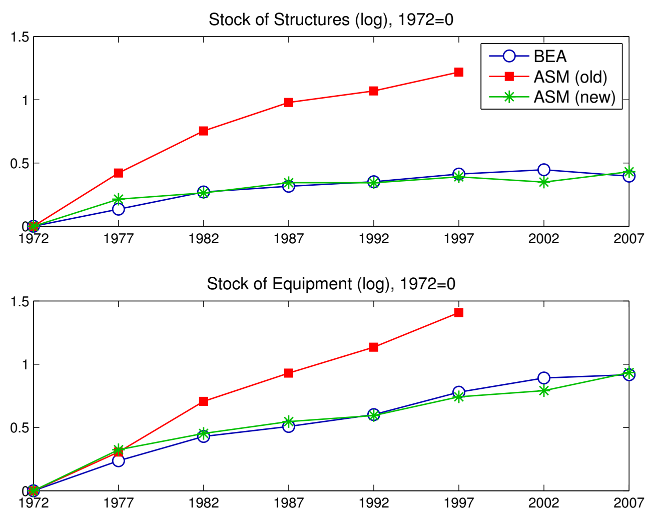

FIGURE 8: AGGREGATE CAPITAL STOCK IN U.S. MANUFACTURING

Note: Capital stocks of the U.S. manufacturing sector published by BEA (blue circles), aggregating the old (red squares) and my refined (green stars) capital stock data in the CMF/ASM. Normalised to 0 in 1972. Clearly visible that the trend growth is off in the old ASM capital measures.

In a similar vein, I find that the old investment measure for equipment is off the benchmark as well, while structure investment comes fairly close. For this I have no other explanation than that the price indices for investment were revised very often.

In many years, (esp. 1972-1976) beginning-of-year capital stocks are not or only partially measured. I can use the end-of-year capital stock from the previous year as far as that is available. This usually leads to some hundreds replacements per year, but to many more in 1973 (24k) and 1982 (9k). In all years subsequent to a Census year and after 1988 (when annual measurement of `BAB` and `MAB` stops), we can naturally impute the beginning-of-year capital stock in this way for almost all observations (50-60k observations).

A.4.2 Accounting for capacity utilisation

In addition to the capital stock available to the establishment, we need to know the utilisation of this capital stock to determine the capital services going into production. As pointed out in previous research (see for example Jorgenson and Griliches (1967); Basu (1996); Burnside, Eichenbaum and Rebelo (1995)), failure to control for capacity utilisation will bias TFP to be more procyclical than it actually is because measured TFP merely reflects unmeasured (procyclical) capacity utilisation. If capacity utilisation rates become more heterogeneous in a downturn, then measured dispersion in TFP would just be a figment of specification error. Burnside, Eichenbaum and Rebelo (1995) have suggested to use electricity or energy instead of capital. The idea in that paper is that energy/electricity is predominantly used to power capital, so variations in energy used will be a good approximation for capacity utilisation. Using energy instead of capital stocks may have the advantage that one measures actual capital services, but, on the other hand, this approach assumes constant energy efficiency. Without further knowledge of the capital stock's energy efficiency one cannot distinguish highly energy efficienct machines running at high capacity of low energy efficiency machines running at low capacity. The capital services supplied by the former are higher for two reasons: more energy-efficienct machines are presumable newer, so their productivity is likely to be much higher. Second, these more productive machines are running at full capacity. For those reasons, I gladly make use of the directly observed capacity utilistion measure from the Plant Capacity Utilisation Survey (PCU). The PCU is a subset of the ASM/CMF and collects explicit information on the utilisation of an establishment's existing capacities. This allows me to construct an explicit capital services measure and omit the energy/electricity inputs that are implicit in the utilisation rates.

Utilisation rates in the PCU are only observed for a small subsample of the data in the ASM/CMF (for about 280k of 4m observations total). I therefore use the data in the PCU to compute industry-wide utilisation rates and use them as a proxy for the other establishments. The idea is that increased demand for a certain good makes most establishments in this industry run at higher capacity.[56] This works for all years after 1974 when the PCU started. For 1972/73,

[56]Of course, this is not true if even within an industry products are imperfect substitutes due to transportation or branding.

I use utilization rates computed by the Federal Reserve Board[57].

So far, I have outlined how to compute the utilised replacement value in constant dollars of the capital stock the firm *owns*. In addition to its on capital stock, an establishment may rent capital to produce. It would be ideal to deduce the real amount of rented capital and include it into the capital measure. Due to data limitations, I have to omit this step: Rented capital is only reported in the years until 1988 and rental payments are hard to transfer into units that correspond to the constant-dollar measure used for the establishment's own capital stock.

A.5 Measurement of materials input

Materials are purchased on the market (materials&parts, `CP`, contract work, `CW`) or come from the materials inventory and are then used in production. Measurement is complicated by the fact that materials inventories (`MIB` and `MIE`) comprise both materials and fuels. Therefore, I have to make an assumption about how much of changes in material inventories are driven by changes in fuel inventory. I assume that all changes in materials inventory are due to changes in materials, while the stock of fuels stays constant. Given the fact that several fuels are storable only at high cost (e.g., natural gas) this seems like a reasonable assumption. Then, I can express the value of materials used in the production process (`VM`) through the inventory identity

$$\begin{aligned} \mathtt{MIE} &= \mathtt{MIB} + (\mathtt{CP} + \mathtt{CW} - \mathtt{VM}) \times \frac{\mathtt{PIMI}}{\mathtt{PIMAT}} \\ \Leftrightarrow \mathtt{M} \equiv \frac{\mathtt{VM}}{\mathtt{PIMI}} &= \frac{\mathtt{MIB} - \mathtt{MIE}}{\mathtt{PIMI}} + \frac{\mathtt{CP} + \mathtt{CW}}{\mathtt{PIMAT}}. \end{aligned} \tag{32}$$

As with goods inventories above, inflows into materials inventories have to be deflated by market prices (`PIMAT`), while materials stocks have to be deflated by inventory prices (`PIMI`). The former comes from the NBER productivity database, the latter could in part be obtained on the industry level from BLS's multifactor productivity tables. As with goods inventory deflators above, these are only available since 1987 and for the same reasons as above I approximate `PIMI` with `PIMAT`.

A.6 Measurement of energy input

I use several measures of energy inputs: electricity, fuels and a combination of them.

[57] Industrial Production and Capacity Utilization – G.17; compiled by the Federal Reserve; downloaded at http://www.federalreserve.gov/datadownload/Build.aspx?rel=G17.

A.6.1 Electricity

Electricity used in the production process ($\mathtt{EL}$) is easily measured. It consists of the quantity of purchased electricity ($\mathtt{PE}$) and the difference between generated and sold electricity ($\mathtt{GE} - \mathtt{SE}$). Since electricity is hardly storable, we do not have to worry about something like an electricity inventory:

$$\mathtt{EL} = \mathtt{PE} + \mathtt{GE} - \mathtt{SE}. \tag{33}$$

For later purposes, it makes sense to impute a price for electricity the establishment pays: $\mathtt{PIEL} = \frac{\mathtt{EE}}{\mathtt{PE}}$. N.B.: If $\mathtt{GE} = \mathtt{0}$, then the fuel used for electricity generation ($\mathtt{VFEL}$) is zero as well.

A.6.2 Fuels

Fuels used in production (nominally expressed as $\mathtt{VF}$) can come from fuel purchases ($\mathtt{CF}$) or from the materials/fuels inventory. As outlined above, I assume that any change in materials inventory ($\mathtt{MIE} - \mathtt{MIB}$) is due to materials only and that the fuel stock in the inventory stays constant. Then, fuel purchases can be used in the production process (oil used to produce plastics) or for electricity generation (oil burned in an electricity generator). The latter quantity is not observed, but must be zero for the vast majority of observations that do not produce any electricity; for those observations $\mathtt{VF} = \mathtt{CF}$. If this is not the case, then I assume that generated electricity is produced with a linear technology. In particular, I assume that 1$ of fuel expenditures can be converted into electricity that could be sold for 1$ (taking into account overhead etc). The idea is that a firm will only find it profitable to produce its own electricity rather than purchasing it when the price of fuel (contained in $\mathtt{VFEL}$) relative that of electricity is not too high and that it can relatively easily substitute among different fuels. $\mathtt{GE} = \frac{\mathtt{VFEL}}{\mathtt{PIEL}} \Leftrightarrow \mathtt{VFEL} = \mathtt{GE} \times \frac{\mathtt{EE}}{\mathtt{PE}}$. Fuel used in production ($\mathtt{F}$) equals the value of fuels ($\mathtt{VF}$) deflated by the energy price index $\mathtt{PIEN}$,

$$\begin{aligned}
\mathtt{VF} &= \mathtt{CF} - \mathtt{VFEL} \\
\mathtt{VF} &= \mathtt{CF} - \mathtt{GE} \times \frac{\mathtt{EE}}{\mathtt{PE}} \\
\mathtt{F} &\equiv \frac{\mathtt{VF}}{\mathtt{PIEN}} = \frac{\mathtt{CF} - \mathtt{GE} \times \frac{\mathtt{EE}}{\mathtt{PE}}}{\mathtt{PIEN}}
\end{aligned} \tag{34}$$

where I assume that the price for fuels equals $\mathtt{PIEN}$, the price deflator for overall energy from the NBER-CES database.

A.6.3 Total energy

Again, I assume that fuels inventory (recorded as part of materials inventory in the ASM/CMF) is unchanged. This means that all fuel purchases are immediately consumed in production or in electricity generation. Total energy expenditures ($\texttt{VE}$) comprise those for fuels ($\texttt{CF}$) and electricity ($\texttt{EE}$); the nominal value is:

$$\begin{aligned}\texttt{VE} &= \texttt{CF} + \texttt{EE} \\ \texttt{E} &\equiv \frac{\texttt{VEN}}{\texttt{PIEN}} = \frac{\texttt{CF} + \texttt{EE}}{\texttt{PIEN}}\end{aligned} \tag{35}$$

where I use $\texttt{PIEN}$, the industry-specific energy price deflator from the NBER-CES productivity database, to obtain real energy input, $\texttt{E}$.

A.7 Construction of cost shares

The baseline estimation described in Appendix C.3 requires knowing the cost shares of factor inputs. They are constructed as follows

$$\begin{aligned}c_L &= \frac{\texttt{SW}}{TC} \\ c_K &= \frac{rK}{TC} \\ c_M &= \frac{\texttt{VM}}{TC} = \frac{\texttt{CP} + \texttt{CW} + \texttt{MIB} - \texttt{MIE}}{TC} \\ c_E &= \frac{\texttt{VE}}{TC} = \frac{\texttt{CF} + \texttt{EE}}{TC} \\ TC &= \texttt{SW} + rK + \texttt{VM} + \texttt{VE}.\end{aligned}$$

All variables are expressed in period-t nominal costs and except r and K are observed in the original dataset. K is the real capital stock (in year-2005 dollars) constructed as described in Appendix A.4, r_t denotes the *nominal* rental rate (year-t dollars rent paid per one year-2005 dollar worth of capital). Multiplying this rental rate, r_t, by the real capital stock, K_t, gives the nominal period-t capital cost of financing the stock in period t. This makes it accord with the other nominal values. The rental rate is constructed from the BLS Capital Tables[58] by dividing corporate capital income (Table 3a) by the real capital stock (Table 4a). The latter variable is expressed in constant (year-2005 dollar), while the former is expressed in current-period dollars, so rK are the capital cost expressed in period-t dollars. Note that capital cost merely includes rent and depreciation, not physical utilisation cost which is captured in the energy cost share.[59] Table 9 displays industry summary statistics on the average plant variables.

[58] "Capital by Asset Type for NIPA-level Manufacturing Industries" downloaded from http://www.bls.gov/mfp/mprdload.htm.

[59] This obviously assumes that depreciation is not influenced by utilisation.

Table 9: Summary statistics: Average plant size in industries

NAICS	Industry	Gross Output	Value Added	Capital	Hours worked	Materials	Energy
311	Food	60.1	23.6	25.4	372.2	35.3	1.1
312	Beverage and tobacco	139.6	97.2	61.6	389.9	41.3	1.1
313	Textiles and fabrics	26.3	10.3	28.4	540.5	14.8	1.1
314	Textile mill products	23.8	10.3	10.5	306.5	13.0	0.4
315	Apparel and accessories	10.9	5.6	2.9	272.7	5.2	0.1
316	Leather and allied products	18.3	9.0	5.8	406.5	9.1	0.2
321	Wood products	18.0	7.3	10.3	201.6	10.2	0.4
322	Paper	56.1	26.9	60.2	407.0	25.9	3.2
323	Printed matter	14.3	8.8	8.9	195.1	5.3	0.2
324	Petroleum and coal	351.9	47.1	198.0	552.2	292.4	12.4
325	Chemical products	97.6	54.2	71.2	383.3	39.1	4.2
326	Plastics and rubber	29.8	14.3	20.2	340.2	14.7	0.8
327	Nonmetallic minerals	17.4	9.8	19.7	191.8	6.0	1.5
331	Primary metals	71.8	24.7	63.3	477.8	43.2	3.9
332	Fabricated metals	23.9	13.1	12.1	278.2	10.3	0.4
333	Machinery	38.5	20.6	17.6	383.7	17.5	0.4
334	Computer and electronics	52.4	32.6	38.6	889.5	19.1	0.6
335	Electrical equipment	45.2	23.5	22.2	550.8	21.0	0.7
336.1-3	Motor vehicles	113.3	40.3	47.5	689.5	72.0	1.0
336.4-9	Other transportation eqpmt.	159.1	94.3	61.4	1,348.5	63.4	1.3
337	Furniture	18.2	10.3	7.7	306.6	7.7	0.2
339	Misc. manufacturing	19.0	12.2	8.0	250.1	6.6	0.2
Non-Durable		60.3	25.1	37.7	357.8	33.3	1.9
Durable		41.8	20.7	23.1	426.3	20.2	0.8
Total Manufacturing		50.0	22.6	29.6	0.4	26.1	1.3

Note: Panel descrition see Table **??**. Average annual value of inputs and outputs of an ASM establishment per industry. Gross output, Value Added, Capital, Materials and Energy are expressed in thousand year 2005-dollars, Hours Worked in thousand hours.

B Empirics – details

B.1 Correcting the productivity estimate

In contrast to looking at the dispersion of TFP growth rates, analysing TFP levels is not as straight-forward. The distribution of TFP levels is likely to differ substantially across industries in terms of the central and higher moments which reflects the industry's technological and competitive environment. Changes in the industry-level TFP dispersion might hence not be observed by just looking at the entire cross section, a problem that did not appear in the cross-sectional dispersion of growth rates. For that reason, I will have to look at cross-sectional dispersion *within* industries. The definition of industry should be narrow enough to overcome this between industry heterogeneity as far as possible. 6-digit NAICS level industries are feasible in my data and should be reasonably narrow. Still, some of the remaining within-industry level heterogeneity might be driven by differences in the type of products rather than productivity. I am aware of this limitation, but the limitation of data do not permit a more in-depth analysis.

The plant-level productivity has to be corrected in several ways. First, it needs to be detrended, second, recentered at zero, thirdly scaled by the long-run variance. These normalisation steps warrant more explanation. First, industries may well have different long-run productivity growth. As a result, industries that diverge more and more form the average growth trend (think semiconductors) are more and more important in determining the cross-sectional dispersion. To correct for that, I fit a simple econometric model with a linear trend. This trend is allowed to differ across industries: $a_{ijt} = g_j t + z_{ijt}$ The resulting term z_{ijt} reflects productivity dispersion around the industry's long-run growth trend. It still needs to be corrected in more ways to obtain a proper cross-sectional dispersion measure $Disp_t$:

$$Disp_t \equiv Median_t \left[Var_{jt} \left(\frac{z_{ijt} - \overline{z}_j}{\sigma_j} \right) \right] \tag{2}$$

As Figure 9 (a) illustrates, different industries may have a different average *level*, $\overline{z}_j$, of productivity even after correcting for the growth *trend*. Changes in the overall cross-sectional dispersion could hence be driven by changes in "outlier" industries. I hence normalise each industry by its long-run industry mean, $\overline{z}_j$. The effect of this step is illustrated in Figure 9 (b).

Finally, it is well-known that the within industry productivity dispersion varies greatly. Syverson (2004) reports that, in a cross section, the within-industry dispersion varies greatly across industries. Some industries like cement are very spread-out in general while highly competitive industries are more compressed. As a consequence, I scale each industry by its long-run standard deviation σ_j. This scaling step is illustrated in Figure 9 (c). Note that the industry mean and standard deviation used in steps 2 and 3 are not dependent on time t. Otherwise, any time variation in dispersion would be lost. As an additional step, I also consider

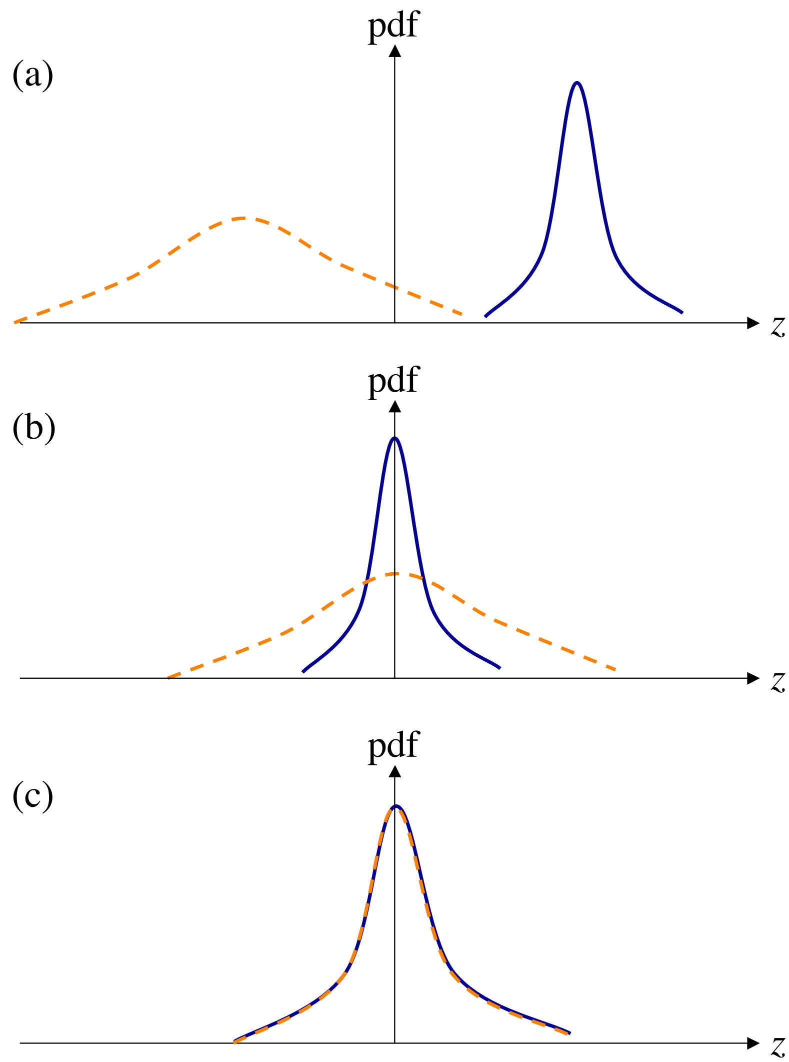

Figure 9: Industry differences in productivity dispersion

Note: Recentering and scaling of industry productivity dispersion makes dispersion industries comparable among each other and over time.

correcting for the long-run skewness. While the typical industry has some positive skew, the results from correcting for skewness and not are very similar.

B.2 Measurement error

The inputs and outputs in equation (1) could be measured imperfectly and bias my empirical results about productivity dispersion. Measurement error is only a problem if it is cyclical in a way that could generate the observed cyclicality in cross-sectional productivity dispersion. With that in mind, I will address possible sources of measurement error. Inputs on the right hand side of equation (1) may be mismeasured (mismeasurement or misreporting on the plant level or mistabulations at the statistical agency). Similarly, establishment-specific inputs prices in capital, materials and energy will have the same effect as mismeasurement. Census claims that of the variables in (1) the output and labour variables are measured fairly well. Along with Foster, Haltiwanger and Syverson (2008) I follow that view and focus on measurement error in materials, energy and capital. As an example, I highlight the effect so measurement error in capital, though the same reasoning holds for the other inputs. Suppose I measure capital with a relative error, so the true capital stock K is mismeasured as $\tilde{K} = K(1+\varepsilon^k)$. Mismeasurement in capital can arise form within-industry differences in capital-embodied technical change and ε^k is a percentage deviation how much the quality-adjusted capital stock is misreported or by how much it differs across plants within an industry. Omitting other input factors for simplicity (the same logic will hold) and expressing measured TFP in logs, we have (omitting indices for readability):

$$\begin{aligned}\tilde{a} &= y - \beta^k \left(k + \varepsilon^k\right) \\ &= a - \beta^k \varepsilon^k\end{aligned}$$

where $\tilde{a}$ is the measured productivity and a actual productivity which we do not observe. I assume that the measurement error in one input is orthogonal to output and other inputs: $E[\varepsilon^r \varepsilon^s] = 0 \;\; \forall r, s = y, k, l, m, e, \; r \neq s$. Then, my dispersion measure, the cross-sectional standard deviation of TFP, is

$$SD(\tilde{a}) = \sqrt{V(\tilde{a})} = \sqrt{V(a) + (\beta^k)^2 V(\varepsilon^k)}$$

On average, the cross-sectional dispersion is 10% higher in a recession than in a boom.

$$SD(\tilde{a}^{rec}) = 1.1 SD(\tilde{a}^{boom})$$

Could this cyclicality be driven by cyclical measurement error? In the worst case, the cross sectional variation in true productivity, $V(a)$, remains constant and all the measured increase in $SD(\tilde{a})$ is due to an increase in measurement error $V(\varepsilon^k)$. If so, by what factor $\xi > 1$ would $SD(\varepsilon^k)$ have to be more spread-out in a recession than in a boom: $\xi SD(\varepsilon^{k \text{ boom}}) = SD(\varepsilon^{k \text{ rec}})$?

$$\begin{aligned} SD(\tilde{a}^{\text{rec}}) &= 1.1 SD(\tilde{a}^{\text{boom}}) \\ \Leftrightarrow \sqrt{V(a) + \xi^2(\beta^k)^2 V(\varepsilon^{k \text{ boom}})} &= 1.1\sqrt{V(a) + (\beta^k)^2 V(\varepsilon^{k \text{ boom}})} \\ \Leftrightarrow \xi^2(\beta^k)^2 V(\varepsilon^{k \text{ boom}}) &= 0.21 V(a) + 1.21(\beta^k)^2 V(\varepsilon^{k \text{ boom}}) \\ \Leftrightarrow \xi &= \sqrt{\frac{0.21}{(\beta^k)^2}\frac{V(a)}{V(\varepsilon^{k \text{ boom}})} + 1.21} \end{aligned} \tag{36}$$

As we can see from equation (36), the smaller β^k and the larger $V(a)/V(\varepsilon)$, the larger are the upswings in measurement error that are required in order to explain the measured increase in productivity dispersion.

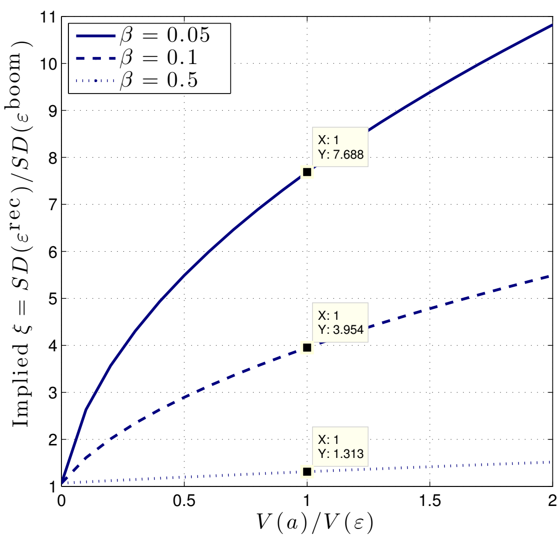

Figure 10: The effect of measurement error

Figure 10 displays quantitative examples for this relationship. In the case of capital, for example, $\beta^k \approx 0.05$ (see Table 10). If one assumes $V(a)/V(\varepsilon) = 1$, i.e. in a boom, mismeasurement is as strong as the true productivity dispersion, then the measurement error in capital has to increase 7.5-fold in order to explain the 10% rise in the measured cross sectional productivity dispersion! Note that these quantitative experiments are a lower bound because I made two very negative assumptions: All of observed dispersion cyclicality is exclusively due to cyclical measurement error and $V(a)/V(\varepsilon) = 1$ looks like a strong assumption too. A similar argument holds for measurement error in materials. Because the coefficient estimate on materials is larger ($\beta^m \approx 0.5$), upswings of "only" 30% in mismeasurement would be sufficient to overturn my results. While I do not deny the possibility of cyclical measurement error driving some of my results, it is hard to believe that the observed dispersion dynamics are entirely driven by mismeasurement of the indicated magnitude.

C Further results

C.1 Returns to scale

The dispersion estimates about productivity are the main interest of this paper. They result from a production function estimation and I will display these results. Be reminded that I measure labour as hours worked, materials as the real value of materials used, capital as a quality-adjusted constant-dollar valued assets and energy as electricity. I do not find systematic differences separating hours worked into white collar vs. blue collar workers. As an alternative to energy used, I also used electricity, but this, too, does not change the results significantly. I use the above-described OP procedure to estimate equation (1') separately for durable and non-durable industries. There has been a large body of research suggesting differences in the technology between those two sectors. Therefore, it makes sense to estimate returns to scale and plant-level productivity separately for durables and non-durables. Table 10 displays the results of this regression in durables goods industries (NAICS 321, 327-339) and the analogous results for non-durables (NAICS 311-316, 322-326).

Table 10: Returns to scale in non-durables and durables

Input	Coefficient estimates ...	
	Non-durables	Durables
Capital	0.101***	0.053***
	(0.002)	(0.010)
Hours Worked	0.235***	0.292***
	(0.002)	(0.007)
Materials	0.471***	0.520***
	(0.001)	(0.006)
Energy	0.104***	0.077***
	(0.001)	(0.001)

Note: *, **, *** significantly different from 0 at the 10%, 5%, 1% level, respectively. Dispersion measures defined analogously to equation (2); description of standard errors see Figure 4.

The coefficients on the input factors are consistent with previous estimates on the industry-level. They are also close to the empirically observed cost shares.[60] Compared to the cost shares, the coefficient on the capital stock is smaller than the capital cost share and the coefficient on energy is larger than the energy cost share. This suggests that the capital stock per se is not productive and energy picks up the effects of the *utilised* capital stock. This result confirms the findings of Burnside, Eichenbaum and Rebelo (1995) who claim that electricity accurately measures capital services. Taken together, the coefficients of capital and electricity add up to a value that is close to the empirically observed cost share of capital.

Returns to scale in non-durables are constant. The production function coefficients sum up to slightly less than unity. In non-durables returns to scale are decreasing (around 0.9) while durable manufacturing is closer to constant returns to scale (around 0.95). These findings are obtained using plant-level data and they conform well with previous research by Basu and Fernald (1995); Burnside, Eichenbaum and Rebelo (1995); Harrison (2003) who also find higher returns to scale in durable manufacturing. This finding will play an important role in explaining differences in the cyclicality of productivity dispersion below. The results of near constant returns to scale in durables and slightly decreasing returns to scale in non-durables is consistent with a fixed factor of production in durables and otherwise constant slightly decreasing returns to scale. Example of fixed factors of production can be overhead labour or capital such as managers or capital structures.

Note that my results do not claim that fixed factors of production are absent in non-durable goods industries. Higher estimated returns to scale in durables are consistent with the view that fixed factors of production are more prevalent in durables than in non-durable goods industries. Related research has found evidence supporting this result. Eisfeldt and Papanikolaou (2010) for example find that levels of organisational capital or intangible assets such as know-how or supply chain networks tend to be more prevalent in durable goods industries.

C.2 Long-run changes in productivity dispersion

Figure 11 displays the time series of productivity dispersion before HP-filtering. Quite remarkably, the long-run pattern of productivity dispersion in both durables and non-durables goods industries changes over time. Over the entire sample, it doubles in both durables and non-durables. The growth in long-run dispersion is a bit stronger in the 1970's, 1980's and 2000's then in the rather sluggish 1990's. Similar long-run changes have been noted in Beaudry, Caglayan and Schiantarelli (2001). They examine the dispersion of firm-level profit *rates* in the UK and find a U-shaped pattern. They explain the long-run changes with learning in the face of macro uncertainty due to policy changes. The same macro-level uncertainty and learning could drive productivity dispersion in the U.S, but my sample is missing the downward-sloping

[60] As an alternative an robustness check, I infer productivity by subtracting cost-weighted inputs from output. These results are displayed in Appendix C.3.

part of the U shape. This is not too surprising because my sample starts later than the UK panel these authors are using.

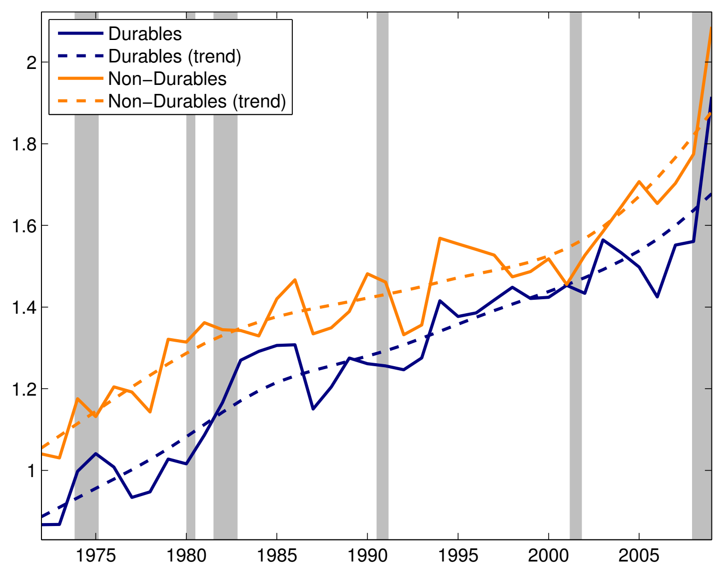

Figure 11: Trends and cycles in dispersion

C.3 The dispersion of Solow residuals

The approach to identify production elasticities with cost shares is attractive because it merely requires the assumptions of constant returns to scale and competitive factor markets.

The structural estimator proposed by Olley and Pakes (1996) is attractive, for it permits estimation of plant-level productivity while solving the endogeneity problem. It is, however, subject to some assumptions about timing of input choices and strong monotonicity of investment in productivity. Especially the latter assumption seems strong and non-convex adjustment costs are a simple (and plausible – see Cooper and Haltiwanger (2006)) example that would lead to lumpy investment and violate the strong monotonicity. The estimation then has to discard all observations with zero investment. In my sample, this is only the case for 12.4% of all observations, so by using the Olley-Pakes estimator I do not have to discard a lot of observations. Nevertheless, I want to make sure that my results are not specific to this estimation technique which relies on specific structural assumptions.

A long-standing tradition in the productivity literature consists of identifying a_{ijt} from Solow residuals.This approach requires assuming constant returns to scale and competitive factor markets. These assumptions look reasonable given that I found close to constant returns to scale in Section C.1. They are also in line hat many other people have found empirically, see for example Burnside, Eichenbaum and Rebelo (1995); Burnside (1996); Basu and Fernald (1997) for industry-level evidence and Lee and Nguyen (2002) for plant-level evidence in the clothing industry. The most important upside is that there are no further assumptions about the timing of input choice and the dependency of investment on productivity. The downside in the context of this paper is that constant returns to scale are inconsistent with the fixed overhead factor in my model. Still, I present the dynamic properties of productivity dispersion when inferred from Solow residuals.

Under the above two weak assumptions, production elasticities can be identified from cost shares.[61] The production function can be rewritten as follows

$$\begin{aligned} y_{ijt} &= a_{ijt} + \beta^k k_{ijt} + \beta^l l_{ijt} + \beta^m m_{ijt} + \beta^e e_{ijt} \\ &= a_{ijt} + c_j^k k_{ijt} + c_j^l l_{ijt} + c_j^m m_{ijt} + c_j^e e_{ijt} \end{aligned}$$

where the cost shares are defined in Section A.7. I assume that these cost shares are constant within 6-digit NAICS industries. This again reflects the idea that the production technology of an industry is constant. As above, we still need to detrend a_{ijt}, recenter and scale the residual z_{ijt} as described in B.1. Note that the capital cost share is composed of the cost for both structure and equipment capital (which have very different rates of return r_t): $c_j^k = \frac{r_{jt}^{ks} K_t^s + r_{jt}^{ke} K_t^e}{Cost_{jt}}$. I use cost shares on the 6-digit NAICS level to account for fine differences in the production structure of indstries. Table 11 gives an overview of cost shares on the 3-digit NAICS level so that the reader may get an impression of the heterogeneity.

Results Like in the main body of the paper, I correlate the HP-100 filtered deviations of the $Disp_t^n$ and $Disp_t^d$ measures with industrial output. Recall that the cleansing view posits dispersion going down in a recession. What we see in Figure 12, however, looks again like the opposite. Rather, the overall time series look similar to the one constructed from Olley-Pakes residuals. Although dispersion is not as volatile, the peaks of the time series still coincide with NBER recessions. Interestingly, dispersion in non-durables does not spike in 2008/09 as it did with the Olley-Pakes productivity estimates.

The overall results of productivity dispersion constructed from Solow residuals conform well with those constructed from Olley-Pakes estimates. As Figure 13 and Table 12 show, dispersion is still strongly countercyclical in durables and weakly countercyclical in non-durables. As Table 13 shows, the countercyclicality is pervasive in various dispersion measures throughout the productivity distribution. Again, Table 14 shows that productivity dispersion is negatively

[61] Firms FOC dictate that factor prices are equal to marginal products $w = \partial Y/\partial L = \beta^l Y/L$. Labour costs are then αY and similarly for the other inputs. If all production elasticities sum to unity, then the cost share is $c_L = wL/Cost = \beta^l Y/[(\beta^k + \beta^l + \beta^m + \beta^e)Y] = \beta^l$.

Table 11: Summary statistics of ASM panel: Cost shares

NAICS	Industry	Labour	Capital		Mat.	Energy
			Str.	Eqp.		
311	Food	0.13	0.06	0.07	0.72	0.02
312	Beverage and tobacco	0.13	0.10	0.10	0.66	0.01
313	Textiles and fabrics	0.20	0.04	0.05	0.65	0.04
314	Textile mill products	0.28	0.02	0.02	0.66	0.02
315	Apparel and accessories	0.27	0.02	0.03	0.68	0.01
316	Leather and allied products	0.34	0.03	0.03	0.57	0.01
321	Wood products	0.20	0.03	0.04	0.70	0.02
322	Paper	0.18	0.02	0.07	0.67	0.02
323	Printed matter	0.37	0.03	0.05	0.52	0.02
324	Petroleum and coal	0.11	0.05	0.07	0.72	0.03
325	Chemical products	0.14	0.10	0.13	0.57	0.04
326	Plastics and rubber	0.22	0.04	0.10	0.60	0.03
327	Nonmetallic minerals	0.28	0.06	0.10	0.45	0.07
331	Primary metals	0.16	0.03	0.04	0.68	0.04
332	Fabricated metals	0.30	0.04	0.08	0.55	0.02
333	Machinery	0.31	0.03	0.06	0.59	0.01
334	Computer and electronics	0.35	0.02	0.04	0.56	0.01
335	Electrical equipment	0.23	0.04	0.07	0.62	0.01
336.1-3	Motor vehicles	0.21	0.02	0.06	0.70	0.01
336.4-9	Other transportation eqpmt.	0.30	0.03	0.04	0.61	0.01
337	Furniture	0.31	0.04	0.05	0.57	0.02
339	Misc. manufacturing	0.32	0.06	0.07	0.52	0.02
Total Manufacturing		0.25	0.04	0.06	0.61	0.02
Average Non-durable Manufacturing		0.17	0.05	0.12	0.60	0.02
Average Durable Manufacturing		0.27	0.04	0.10	0.55	0.02

Note: Cost shares on the 3-digit NAICS industry level in the ASM panel, averaged over the years 1972-2009. Construction of cost shares described in A.7.

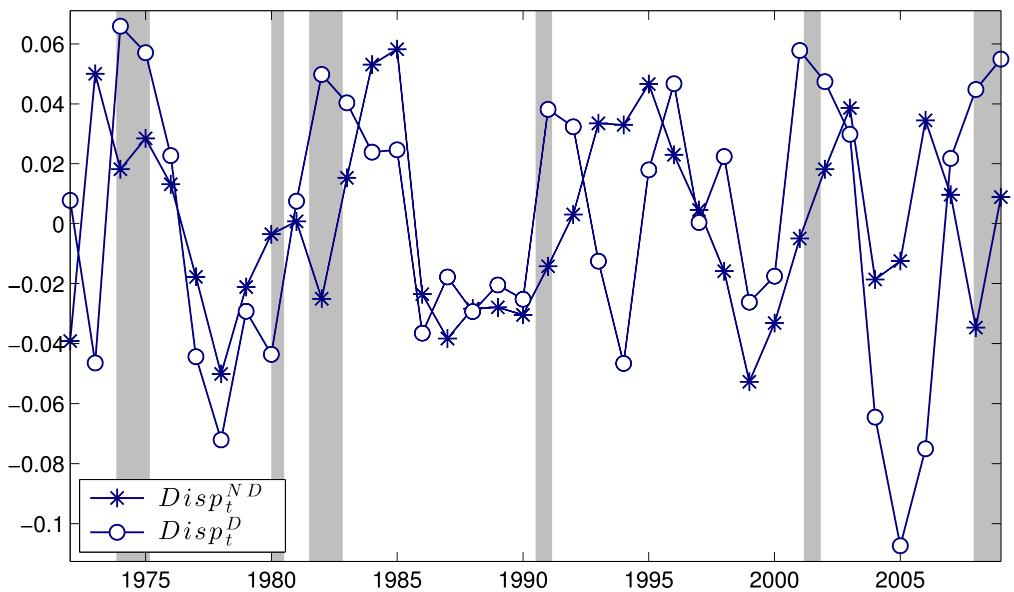

Figure 12: Productivity dispersion – Solow residuals

Note: Time series plot of the cyclical components of output and productivity dispersion in durable goods producing manufacturing. The dispersion measure is as defined in equation (2). Left panel displays non-durables, right panel displays durables, shaded bars denote NBER recessions.

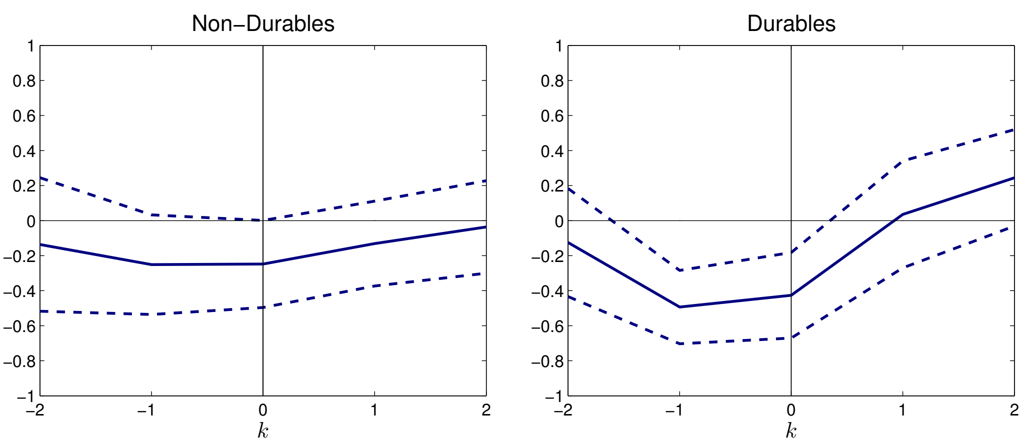

Figure 13: Cyclicality of productivity dispersion – Solow residuals

Note: Correlograms display the correlation between the cyclical component (HP-100 filtered time series) of output and productivity dispersion in non-durables and durables respectively: $Corr(Y_t, Disp_{t+k})$. Dispersion measures defined analogously to equation (2); description of standard errors see Figure 4.

Table 12: Cross-correlations of dispersion – Solow residuals

Lead/Lag	Correlation of output and dispersion in ...	
	Non-durables	Durables
-2	-0.136	-0.125
	(0.194)	(0.157)
-1	-0.252*	-0.494***
	(0.145)	(0.107)
0	-0.248*	-0.426***
	(0.127)	(0.125)
1	-0.131	0.036
	(0.124)	(0.156)
2	-0.036	0.245*
	(0.135)	(0.140)

Note: *, **, *** significantly different from 0 at the 10%, 5%, 1% level, respectively. Dispersion measures defined analogously to equation (2); description of standard errors see Figure 4.

correlated with a variety of the business cycle. The striking similarity between the dispersion measures, once constructed from Olley-Pakes estimates, once from Solow residuals, suggests that the overall negative correlation of dispersion with the business cycle is robust to the specific method used.

Table 13: Correlation of dispersion measures and output – Solow residuals

Correlation of output in with cross-sectional...	Non-durables	Durables
Variance	-0.242	-0.49***
	(0.168)	(0.098)
Standard Deviation	-0.248*	-0.426***
	(0.127)	(0.125)
Inter-quartile range	-0.136	-0.447***
	(0.155)	(0.098)
Inter-decile range	-0.187	-0.473***
	(0.188)	(0.094)

Note: *, **, *** significantly different from 0 at the 10%, 5%, 1% level, respectively. Dispersion measures defined analogously to equation (2); description of standard errors see Figure 4.

Table 14: Correlation of output measures and dispersion – Solow residuals

Correlation of dispersion in with...	Non-durables	Durables
Production – HP filtered ($\lambda = 100$)	-0.248*	-0.426***
	(0.127)	(0.125)
Production – HP filtered ($\lambda = 6.25$)	-0.029	-0.499***
	(0.164)	(0.114)
Production growth rate	0.085	-0.406***
	(0.16)	(0.148)
GDP – HP filtered ($\lambda = 100$)	-0.213	-0.380***
	(0.171)	(0.128)
GDP – HP filtered ($\lambda = 6.25$)	0.06	-0.537***
	(0.174)	(0.088)
GDP growth rate	0.127	-0.442***
	(0.158)	(0.129)
No. of NBER boom months/year	0.053	-0.441***
	(0.115)	(0.128)
Census rotation years dropped	-0.213	-0.518***
	(0.187)	(0.11)

Note: *, **, *** significantly different from 0 at the 10%, 5%, 1% level, respectively. Dispersion measures defined analogously to equation (2); description of standard errors see Figure 4.

D Detailed solution to the model

First-order conditions

$$
\begin{aligned}
P_t^n \equiv 1 &= \frac{\sigma}{\sigma-1}\frac{w_t}{\overline{z}^n} N_t^{\frac{1}{1-\sigma}} && \text{(Pricing ND Sector)}\\
P_t^d &= \frac{\varrho}{\varrho-1}\frac{w_t}{\overline{z}_t^d}(N_t^d)^{\frac{1}{1-\varrho}} && \text{(Pricing D Sector)}\\
\pi_t &= \pi_t^n + \frac{N_t^d}{N_t}\pi_t^d && \text{(Avge profits)}\\
\pi_t^n(\overline{z}^n) &= \frac{1}{\sigma}\left(\frac{\sigma-1}{\sigma}\frac{\overline{z}^n}{w_t}\right)^{\sigma-1} C_t && \text{(Avge profits in } n\text{)}\\
\pi_t^d(\overline{z}_t^d) &= w_t c_f \frac{\varrho-1}{k+1-\varrho} && \text{(Avge profits in } d\text{)}\\
L_t &= N_t l_t^n + N_t^d l_t^d + N_t^E c_e && \text{(Aggr labour demand)}\\
l_t^n(\overline{z}^n) &= \left(\frac{\sigma-1}{\sigma}\frac{1}{w_t}\right)^{\sigma}(\overline{z}^n)^{\sigma-1} C_t && \text{(labour demand } n\text{)}\\
l_t^d(\overline{z}_t^d, c_f) &= c_f\left[\frac{(\varrho-1)k}{k+1-\varrho}+1\right] && \text{(labour demand } d\text{)}\\
\frac{N_t^d}{N_t} &= \left(\frac{z_L}{\overline{z}_t^d}\right)^k \left(\frac{k}{k+1-\varrho}\right)^{\frac{k}{\varrho-1}} && \text{(Share of firms in D sector)}\\
N_{t+1} &= (1-\zeta)(N_t + N_t^E). && \text{(Dynamics of no. firms)}\\
v_t &= c_e w_t && \text{(Free entry)}\\
\frac{\alpha}{C_t} X_t^{1-\theta} &= \lambda_t(1+\tau_t^c) && \text{(HH FOC: Cons ND)}\\
\lambda_t P_t^d(1+\tau_t^I) &= \beta\left[\frac{\gamma}{D_{t+1}}X_t^{1-\theta} + \lambda_{t+1}P_{t+1}^d(1+\tau_{t+1}^I)(1-\delta)\right] && \text{(HH FOC: Inv durables)}\\
\frac{\psi\phi_t}{1-\phi_t L_t}X_t^{1-\theta} &= \lambda_t w_t && \text{(HH FOC: Intratemp Euler)}\\
\lambda_t v_t &= \beta\mathbb{E}_t\left[(1-\zeta)\lambda_{t+1}(v_{t+1}+\pi_{t+1})\right] && \text{(HH FOC: Intertemp Euler Equity)}\\
w_t L_t + \pi_t N_t &= C_t + P_t^d\left[D_{t+1}-(1-\delta)D_t\right] + v_t N_t^E && \text{(Budget constraint)}
\end{aligned}
$$

Endogenous variables:

$$\overline{z}_t^d, P_t^d, \pi_t, \pi_t^n, \pi_t^d, N_{t+1}, N_t^E, N_t^d, v_t, C_t, D_{t+1}, \lambda_t, L_t, l_t^n, l_t^d, w_t$$

Log-linearised

$$\hat{w}_t = \frac{1}{\sigma - 1}\hat{N}_t \tag{37}$$

$$\hat{P}^d_t - \hat{w}_t + \hat{\tilde{z}}^d_t + \frac{1}{\varrho - 1}\hat{N}^d_t = 0 \tag{38}$$

$$-\hat{\pi}_t + \hat{\pi}^n_t\left(1 - \frac{\overline{\pi}^d\overline{N}^d}{\overline{N}\overline{\pi}}\right) + \left[\hat{N}^d_t + \hat{\pi}^d_t\right]\frac{\overline{\pi}^d\overline{N}^d}{\overline{N}\overline{\pi}} = \hat{N}_t\frac{\overline{\pi}^d\overline{N}^d}{\overline{N}\overline{\pi}} \tag{39}$$

$$\hat{\pi}^n_t - (1-\sigma)\hat{w}_t - \hat{C}_t = 0 \tag{40}$$

$$\hat{\pi}^d_t - \hat{w}_t = 0 \tag{41}$$

$$\hat{l}^n_t\frac{\overline{Nl}^n}{\overline{L}} + \hat{N}^d_t\left(1 - \frac{\overline{Nl}^n}{\overline{L}}\right) + \hat{N}^E_t\frac{c_e\overline{N}^E}{\overline{L}} - \hat{L}_t = -\hat{N}_t\frac{\overline{Nl}^n}{\overline{L}} \tag{42}$$

$$\hat{l}^n_t + \sigma\hat{w}_t - \hat{C}_t = 0 \tag{43}$$

$$\hat{l}^d_t = 0 \tag{44}$$

$$\hat{N}^d_t + k\hat{\tilde{z}}^d_t = \hat{N}_t \tag{45}$$

$$\hat{N}_{t+1} - \delta\hat{N}^E_t = (1-\delta)\hat{N}_t \tag{46}$$

$$\hat{v}_t - \hat{w}_t = 0 \tag{47}$$

$$\hat{\xi}_t + (1-\theta)\hat{X}_t - \hat{C}_t - \hat{\lambda}_t - \hat{\tau}^c_t\frac{\tau^c}{1+\tau^c} = 0 \tag{48}$$

$$\begin{aligned}&\left[\rho^\xi\hat{\xi}_t + (1-\theta)\hat{X}_t - \hat{D}_{t+1}\right][1-\beta(1-\delta)] + ...\\ ...&\left[\hat{\lambda}_{t+1} + \hat{P}^d_{t+1} + \hat{\tau}_{t+1}\frac{\tau^i}{1+\tau^i}\right]\beta(1-\delta) - \hat{\lambda}_t - (1-\rho^b)\hat{b}_t - \hat{P}^d_t - \hat{\tau}^i_t\frac{\tau^i}{1+\tau^i} = 0\end{aligned} \tag{49}$$

$$\hat{\phi}_t\frac{1}{1-\overline{\phi L}} + (1-\theta)\hat{X}_t + \hat{\xi}_t + \hat{L}_t\frac{\phi\overline{L}}{1-\overline{\phi L}} - \hat{\lambda}_t - \hat{w}_t = 0 \tag{50}$$

$$(1-\rho^b)\hat{b}_t + \hat{\lambda}_t + \hat{v}_t - \hat{\lambda}_{t+1} - \hat{v}_{t+1}\frac{\overline{v}}{\overline{v}+\overline{\pi}} - \hat{\pi}_{t+1}\frac{\overline{\pi}}{\overline{v}+\overline{\pi}} = 0 \tag{51}$$

$$\begin{aligned}&-\hat{w}_t\frac{\overline{wL}}{\overline{wL}+\overline{N\pi}} - \hat{L}_t\frac{\overline{wL}}{\overline{wL}+\overline{N\pi}} - \hat{\pi}_t\frac{\overline{N\pi}}{\overline{wl}+\overline{N\pi}} + \hat{C}_t\frac{\overline{C}}{\overline{wl}+\overline{N\pi}} + ...\\ &... + \hat{P}^d_t\frac{\delta\overline{DP}^d}{\overline{wl}+\overline{N\pi}} + \hat{D}_{t+1}\frac{\overline{DP}^d}{\overline{wl}+\overline{N\pi}} + \hat{N}^E_t\frac{\overline{\delta vN}}{(1-\delta)(\overline{wl}+\overline{N\pi})} + ...\\ &\qquad ... + \hat{v}_t\frac{\overline{\delta vN}}{(1-\delta)(\overline{wl}+\overline{N\pi})} = \hat{N}_t\frac{\overline{N\pi}}{\overline{wl}+\overline{N\pi}} + \hat{D}_t\frac{(1-\delta)\overline{DP}^d}{\overline{wl}+\overline{N\pi}}\end{aligned}$$