Essays on Competition, Financial Structure and Productivity

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Abstract

In this thesis I analyze 3 current empirical questions of interest in macroeconomics. The first concerns the effect of competition on cash holdings. The large increase in cash held by US firms has increased interest in competition as a possible driver, with contradictory results in the literature. I show that low profitability firms increase cash as a response to competition, whereas high profitability firms do the reverse. Afterwards, I focus on the effects of financial structure on productivity. An interesting empirical pattern is uncovered: a firm's own debt does not harm its own productivity, but aggregate debt does. The negative relationship is shown to work through a real estate valuation channel. Finally, I uncover short-lived pro-cyclical spikes of adjusted aggregate productivity precisely timed at the beginning and end of recessions. I show that they are likely to be associated with demand-side movements, rather than technology shocks.

Resum

En aquesta tesi analitzo 3 qüestions empíriques actuals d'interès en macroeconomia. La primera tracta sobre l'efecte de la competència en els balanços d'efectiu. El gran increment en l'efectiu en possessió d'empreses dels Estats Units ha dut interès en la competència com a possible causa. En aquesta tesi es demostra que les empreses amb baixos beneficis incrementen el seu efectiu en resposta a més pressió competitiva, mentre que les empreses amb beneficis alts fan el contrari. La segona qüestió és l'efecte de l'estructura financera en la productivitat. Un patró interessant és descobert, el deute d'una empresa no fa baixar la seva productivitat, però sí que ho fa el deute agregat. Aquesta relació sembla causada per un canal basat en els preus immobiliaris. Finalment, es detecten moviments de la productivitat ajustada per utilització, pro-cíclics, poc persistents i durant exactament el principi i el final de les recessions. Aquests semblen causats per factors relacionats amb la demanda, i no factors tecnològics.

Preface

In this thesis I analyze 3 current empirical questions of interest in macroeconomics. The first, analyzed in chapter 1, concerns the effect of competition on cash holdings. Understanding this relationship is important: firm cash holdings as a percentage of total assets in the US increased dramatically from 10.5% in 1980 to 23.2% in 2006 as reported by Bates, Kahle and Stulz (2009). Such an increase can be worrying because it may shift resources from more productive assets to cash. Moreover, Bacchetta, Benhima and Poilly (2014) find a negative co-movement between corporate cash and employment at the aggregate level. Parallel to this trend, trade openness and import penetration have substantially increased – while evidence on markup measures is less clear. This has led to interest in product market competition as an element in explaining the rise in cash holdings. Meanwhile, the literature has identified two main motives for firm cash holding. The first is the precautionary motive. Firms hold cash to cope with adverse shocks, such as operating losses or unexpected costs, and to avoid recourse to more costly external finance funds or costly liquidation. Almeida, Campello and Weisback (2004), Archarya, Almeida and Campello (2006), Han and Qiu (2007) provide examples of the precautionary motive. The second motive is the strategic motive, usually associated with the deep pocket argument. In this case a firm holds cash to reduce competition. Usually a financially constrained firm is predated by an unconstrained rival, for instance as in Benoit (1989) or Bolton and Scharfsteint (1990). In an empirical study Frésard (2010) analyzes the causal impact of cash on product market structure and finds that cash rich firms gain future market share at the expense of rivals, providing evidence in favor of the deep pocket argument. Thus a coexistence of both motives appears plausible. Nonetheless, in the cash and product market competition literature both model predictions and empirical results deliver contradictory results regarding the relationship of cash and competition. The generally labeled precautionary effect predicts a positive relationship between cash holdings and product market competition, whereas the strategic motive generally predicts a negative relationship between cash holdings and competition.

To understand the opposite effects on cash holdings that the strategic motive and the precautionary motive can have I develop a highly stylized partial equilibrium framework. In this model firms can be of high or low markup. In addition, firms can launch R&D campaigns to temporarily boost product quality and face the positive probability of incurring a random cost, which can bankrupt low markup firms. Thus both strategic cash holding, to pay for the R&D campaign, and precautionary cash holding, to pay for the random cost and to avoid bankruptcy, are present in the model. The main results are as follows. First, both types of firms hold cash for strategic motives but only precautionary firms hold precautionary cash. Second, when both motives are present, the precautionary dominates the strategic. Third, precautionary cash decreases with markup as higher revenue lowers the need to save cash to pay for the random cost. Fourth, strategic cash increases with markup. I next turn to an empirical exercise to analyze whether the model conclusions hold, and crucially to test whether the low markup firms will respond to markup increases by decreasing cash holdings and whether the high markup firms will react by increasing cash holdings. Using Compustat firm level data the estimation results are consistent with the model. The effect of the proxy of markup, the Price Cost Margin (PCM), depends on the firm level of the proxy itself, in the manner predicted by the model. Interestingly, results using the whole sample indicate that the precautionary motive dominates. However, when the effect is estimated splitting the sample according to high and low profitability, the strategic motive accounts for most of the cash held.

The second empirical question concerns the effect of financial structure on productivity, and it is the focus of chapter 2. Instead of considering cash as in chapter 1, the variable of interest of financial structure now concerns finance; and debt in particular. The relation between finance and economic growth has been extensively explored theoretically; two excellent reviews are Levine (2005) and Levine (1997). The link between finance and productivity has often been analyzed within the more general scope of economic growth. As framed in Levine (1997), the relation is presented as follows. In a frictionless world, such as in the Arrow Debreu model, the financial system plays no role in improving economic growth. Once frictions exist, finance can improve economic growth via an increase of productivity, capital accumulation, or both. In general, until recently, both theoretical and empirical studies pointed to a positive association between finance and productivity. More recent studies have pointed to the negative relationship between finance and productivity mainly from an empirical point of view. Nonetheless, plausible explanations have been modelled, for instance that the financial sector crowds out workers from other more productive sectors; see Cecchetti and Kharroubi (2015). There are relatively few studies that use micro data to shed light on the relationship between finance and productivity growth. A recent study by Levine and Warusawitharana (2014) is among the exceptions in that it uses firm level data – and shows that there is a positive relationship between debt and future productivity growth. By employing firm level data this chapter shows that idiosyncratic debt is positively associated (but not always significantly) with future idiosyncratic TFP, but aggregate debt has a statistically significant negative impact on future firm level TFP. A hypothesis to explain the negative relationship between aggregate debt and firm level productivity is presented. Debt and real estate prices are positively linked at the aggregate level, while aggregate real estate prices have a negative impact on firm level productivity. The reason is what amounts to (virtually) an accounting identity. Indeed, the results from the empirical exercise lend support to this hypothesis. There is a link between country level debt and real estate valuations, and both tend to have a negative impact on firm TFP. Furthermore, a productivity measure which is robust to real estate valuations does not present the negative impact of aggregate debt on firm level productivity. Finally, splitting the sample according to the "real estate intensity" of the country sector pairs shows that the impact of aggregate debt on firm level TFP is significant and negative for those firms operating in high real estate intensity environments, but is not significant in low real estate intensity ones.

In chapter 3 I study the behavior of adjusted productivity during recessions. There are two crucial differences with respect to productivity as considered in chapter 2. First, it is measured at the quarterly frequency, and so it allows us to examine the business cycle perspective. Second, productivity is adjusted for factor utilization, and so can be considered a better proxy of technological capability. The role of technology shocks in the business cycle is still an actively debated subject in macroeconomics. The results are far from homogeneous and can be categorized into three broad groups. Empirical studies based on long run restrictions assign only a minor role to technology as a driver of the business cycle. This result was first stated in the seminal paper of Galí (1999), and was subsequently confirmed, for instance in Francis and Ramey (2005). Another broad category corresponds to results of medium scale DSGE models. For instance in Smets and Wouters (2007) technology shocks can play a sizable role even in the short run, accounting for 8 to 20% of the variance of output for horizons of one year or less. Finally, at the other end of the spectrum there is the old and new RBC literature. As is well known, the early RBC literature claimed technology as the primary driver of the business cycle. In a more recent contribution, McGrattan and Prescott (2012) replicate the Great Recession on the basis of productivity shocks. In general, Structural Vector Autoregression (SVAR) models tend to grant only a small role to technology shocks at business cycle frequencies, whereas other types of models allow a larger role. The crucial assumption behind the SVAR models is the identification of technology shocks as those having permanent effects. A new database of utilization adjusted productivity produced by Fernald (2012), presents, in principle, the opportunity to identify technology shocks other than through established long-run restrictions. Using this new database Sims (2011) finds that technology shocks can explain up to 60% of the cyclical variations in output. In order to better understand to what extent the short run adjusted productivity movements identified by Sims can really be considered productivity shocks, I analyze in detail the business cycle properties of the Fernald database. Using the new database, I uncover procyclical spikes of adjusted productivity during precisely the turning points of recessions, the 1st quarter of recessions and the 1st quarter of recoveries. Furthermore, the spikes are not observed in the remaining quarters of recessions and recoveries and account for the bulk of the output-adjusted productivity correlation at the quarterly frequency, leaving the rest of the sample with a very low correlation. I show that the procyclical spikes are neither a consequence of co-movements of related variables, nor due to turning points being exceptional periods in any other sense than their definition and the behavior of adjusted productivity. Furthermore, periods similar to turning points in terms of adjusted TFP behavior are very scarce within the US post-war sample.

The potential implications of the procyclical spikes of adjusted productivity for a better understanding of the business cycle are considerable. Given the particular quarters when the productivity movements occur (during turning points), if they are caused by technology shocks, these could be the cause of recessions and recoveries and thus of much of the output variation at business cycle frequencies. Simulations in standard DSGE models show the difficulty of replicating observed output and technology patterns. I conclude, therefore, that technology shocks are unlikely to cause the adjusted productivity spikes observed. As an alternative hypothesis to technology shocks, I examine whether demand can account for the reported empirical patterns. SVAR identified demand shocks are crucial for explaining the behavior of adjusted productivity during turning points. Importantly, steps are taken to ensure that the SVAR estimated demand shocks cannot be plausibly interpreted as technology shocks. Furthermore, two plausible demand indicators present both: procyclical spikes during turning points and a differential correlation with adjusted productivity during these periods. These results diminish the role of technology in the business cycle because the correlation between output growth and adjusted productivity growth is substantially smaller if turning points are removed from the sample. Pending further research, that demand influences adjusted productivity during turning points seems a reasonable, albeit a tentative conclusion.

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1. Disentangling the effects of competition on firm cash holdings

1.1 Abstract

To disentangle the effects of competition on cash holdings is useful to examine two of the different mechanisms through which competition might affect cash holdings. One mechanism stressed by Morellec, Nikolov and Zucchi (2013) is the precautionary motive. The precautionary motive leads firms to hold more cash in response to an increase in competitive pressure to avoid financial distress. The second is the strategic motive stressed by Baskin (1987). If firms engage in what Baskin labels "monopolistic games", and cash holdings can facilitate those campaigns, an increase in monopoly power can lead to an increase in cash holdings. To analyze whether the strategic or the precautionary motive prevails I consider the markup dimension of competition, but consider other dimensions as well. I present a model that predicts the existence of both precautionary and strategic effects within the markup dimension. The estimation results, using a Compustat sample, point to the validity of the model. Furthermore, at the aggregate level the strategic motive is shown to be the dominant one.

1.2 Introduction

In this chapter I present a theoretical model and an empirical exercise to analyze the relationship between cash holding and product market competition. Understanding this relationship is important: firm cash holdings as a percentage of total assets in the US increased dramatically from 10.5% in 1980 to 23.2% in 2006 as reported by Bates, Kahle and Stulz (2009). Such an increase can be worrying because it may shift resources from more productive assets to cash. Moreover, Bacchetta, Benhima and Poilly (2014) find a negative co-movement between corporate cash and employment at the aggregate level.

Second, parallel to this trend, trade openness -Epifani and Gancia (2011)- and import penetration -Boulhol (2010)- have substantially risen. Morellec, Nikolov and Zucchi (2013) find that the Price Cost Margin (PCM) has fallen[1]. This has brought interest in product market competition as an element in explaining the rise in cash holdings. Moreover Bates, Kahle and Stulz (2009) find a positive association between cash flow volatility and cash; and Irvine and Pontiff (2009) argue that more intense product market competition causes greater cash flow volatility suggesting a plausible causal link between competition and cash holdings.

[1]Nerkada and Ramey (2010) find an increasing Price Cost Margin for the same period using BLS instead of Compustat data. See Boulhol (2010) for an explanation of the disconnection between the pro-competitive effects of trade and the Price Cost Margin.

Third, the literature has identified two main motives for firm cash holding. The first is the precautionary motive. Firms hold cash to cope with adverse shocks, such as operating losses or unexpected costs, and to avoid recourse to more costly external finance funds or costly liquidation. Almeida, Campello and Weisback (2004) model the precautionary motive and find that financially constrained firms save out of cash flow, whilst the rest do not. Archarya, Almeida and Campello (2006) find a similar result, as constrained firms with high hedging needs tend to save out of cash flow and do not reduce debt. On the other hand, constrained firms with low hedging needs tend to use cash flow to reduce debt. Han and Qiu (2007) develop a similar model in continuous time, and find that cash flow volatility increases cash holdings for constrained firms. These findings are corroborated by the empirical studies Oper et al. (1999) and Bates, Kahle and Stulz (2009). The second motive is the strategic motive, usually associated with the deep pocket argument. In this case a firm holds cash to reduce competition. The deep pocket argument has usually been formalized with capital structure and not specifically cash. Usually a financially constrained firm is predated by an unconstrained rival, for instance as in Benoit (1989) or Bolton and Scharfsteint (1990). In an empirical study Frésard (2010) analyzes the causal impact of cash on product market structure and finds that cash rich firms gain future market share at the expense of rivals, providing evidence in favor of the deep pocket argument. Thus a coexistence of both motives appears plausible. Nonetheless in the cash and product market competition literature both model predictions and empirical results deliver contradictory results regarding the relationship of cash and competition. On the one hand, the generally labeled precautionary effect[2] predicts a positive relationship between cash holdings and product market competition. The positive relationship arises from the following mechanism: an increase in competition drives down profits thus, increasing the likelihood of financial distress, which, in turn, leads firms to hold more cash. Morellec, Nikolov and Zucchi (2013) stress this motive. In their model, firms hold cash to avoid inefficient liquidation following losses. Using several measures of competition intensity, amongst others the Price Cost Margin, they find compelling evidence in favor of the precautionary effect. Frésard and Valta (2012) find that following a decrease in tariff rates cash holdings increase. Hoberg, Phillips, and Prabhala (2012) develop a proxy of competition which is positively related to cash holdings as well. On the other hand, the strategic motive generally predicts a negative relationship between cash holdings and competition. The negative relationship arises because cash is used as a strategic tool against competitors, and the higher the value of a firm market niche the higher the value of cash. Baskin (1987) presents a model and empirical evidence in favor of the strategic motive. In his model firms engage in what Baskin labels "monopolistic games", campaigns against the entry of competitors, and cash holdings facilitate those campaigns. Thus, a higher monopoly power increases the value of the incumbent position and thus of the cash holdings. The main test is a regression based analysis on whether a proxy of monopoly games significantly influences liquidity holdings. The proxy is constructed as market to book value (Baskin argues that this is a measure of monopoly power) times the sum of R&D and advertising expenditure. The author finds a positive relationship between

[2]A positive relation between competition and cash holdings is often referred to as the precautionary effect, whereas a negative relation is labeled a strategic effect. Nonetheless the denomination is model dependent, Lyandres and Palazzo (2014) find that in their model strategic considerations deliver a positive relation and vice-versa. Nonetheless, I maintain the usual labeling.

monopoly power and cash holdings. In two recent studies, focussing on cash holdings for innovative firms, the results show a more ambiguous answer as to whether cash holdings increase or decrease with competition intensity. Ma, Mello and Wu (2013) find that a higher Price Cost Margin, which they use as a proxy for entry barriers, decreases cash holdings. On the other hand, their proxy for the winner's advantage - following an R&D competition - the skewness of market shares increases cash holdings. Lyandres and Palazzo (2014) construct a measure of competition based on the proximity of firms' patents and find that financially constrained firms hold more cash if they face increased competition, but that unconstrained firms do not.

Based on the above discussion the purpose of this study is twofold. The first is to understand the opposite effects on cash holdings that the strategic motive and the precautionary motive can have, depending on the dimension of competition that is varying. And the second is to establish with markup or profit rate measures (using the Price Cost Margin as a proxy) whether the strategic or precautionary motives coexist and, if so, which is most likely to dominate the overall effect. To this end I develop a theoretical model. This allows me to assess in which cases cash holdings are predicted to increase or decrease in response to competitive pressure. Finally I examine the empirical merit of the model's predictions.

The model follows a highly stylized partial equilibrium framework. Firms face a demand function with constant elasticity of substitution. The markup dimension of competition is simply pinned down by the CES parameter, the consumer's love of variety. In addition, firms can launch R&D campaigns to temporarily boost the quality and, as a consequence, the sales of their product. Firms cannot raise outside funds during each period and campaign payments present a cash-in-advance constraint, thus firms must carry cash to be able to finance their campaigns; the strategic motive for holding cash. Additionally, firms can be of two types, high or low markup - and every type faces a positive probability of incurring a random cost. Crucially, low markup firms do not generate enough revenue to pay the high realization of the cost and avoid liquidation, whilst high markup firms do. In consequence low markup firms -but not high markup firms- have to carry additional cash to cover the high realization of the cost, the precautionary motive of cash holdings. Hence I label high markup firms strategic, and low markup firms precautionary. The main results are as follows. First, both types of firms hold cash for strategic motives but only precautionary firms hold precautionary cash. Second, when both motives are present, the precautionary dominates the strategic. Third, precautionary cash decreases with markup as higher revenue lowers the need to save cash to pay for the random cost. Fourth, strategic cash increases with markup. With this simple setting I am able to analyze the questions of interest by testing the model's predictions: the low markup firms will respond to markup increases by decreasing cash holdings, according to the precautionary motive. On the other hand the high markup firms will react by increasing cash holdings according to the strategic motive[3].

To test these predictions I use Compustat data for the period 1997-2010. The sample consists of approximately 27.000 firm-year observations. To analyze the predictions I run a series of regressions relating cash with controls and intensity of competition measures. Consistent with the aim of the study I control at the same time for markup

[3]Finally, an increase in non-markup competition is not predicted to present a specific sign as it is not modeled.

and another competition dimension, using the Price Cost Margin and the HPP index[4]. Nevertheless the results do not vary qualitatively with respect to running the regressions separately. To analyze the effects of the strategic motive and the precautionary motive I generate two subsamples according to the PCM, one with high PCMs and one with low. This makes it possible to identify the model high and low markup firms with their empirical counterparts. I then run separate regressions for each subsample focusing on the effect of the PCM on cash holdings. This exercise allows me to establish whether indeed the opposite effects of the strategic motive and the precautionary motive are in line with the data.

The estimation results are consistent with the model. The effect of the proxy of markup depends on the PCM of the firm. If the firm has a (relatively) high PCM an increase in markup leads to higher cash holdings, whilst if a firm has a (relatively) low PCM the increase in markup leads to a decrease in cash holdings. Interestingly, results using the whole sample indicate that the precautionary motive dominates, yet, when examining the two subsamples the strategic motive accounts for most of the cash held. The evidence suggests that using the whole sample to assess the relative importance of each motive can be highly misleading. Results suggesting a negative relationship between the PCM and cash held, such as the one in Morellec, Nikolov and Zucchi (2013), should be treated with caution as they crucially rely on observations on a fat left tail of the markup distribution. Finally, for non-markup competition the MNZ result that higher competition is associated with higher cash holdings holds for both subsamples.

This chapter is organized as follows. Section 3 develops the model and states the testable predictions. Section 4 presents the data and the methodology. Finally in section 5 the results are presented and discussed.

1.3 The Model

The model is set as a partial equilibrium, and I only develop the firms' side without taking households into consideration. I develop a variant of a CES demand function. The crucial modification with respect to the standard model is that firms can engage in campaigns that temporarily boost quality, and cash must be held to finance such campaigns. This framework produces a simple model which allows me to analyze simultaneously a positive effect (precautionary motive) and a negative effect (strategic motive) of competition on cash holdings.

The exposition of the model is organized as follows, first, the modification of preferences and its consequences are discussed, second, the problem of the firm is solved, and third, the model predictions are presented.

a) Technology - Temporary boost in quality

A firm has access to a linear production function, to obtain the output good y, by using labor, n, following $y = n$. On the demand side, the firm faces a CES demand function:

[4]The HPP index is thoroughly described in the data section. The index reflects the degree to which a product description of a firm overlaps with the ones of its competitors.

$$y = p^{-\varepsilon} A \left(\frac{\varepsilon}{\varepsilon - 1} \right)^{\varepsilon} \tag{1.1}$$

where ε determines the elasticity with respect to the price, and A indicates the quality of the product under the interpretation that quality increases demand at a fixed price. The additional term, $\left(\frac{\varepsilon}{\varepsilon-1}\right)^{\varepsilon}$, is a useful normalization to achieve that firms have in equilibrium the same output, regardless of the CES parameter. Additionally the firm has access to an R&D campaign that allows to increase the quality parameter. In particular quality in the absence of a campaign is $A=1$, and if the campaign is launched $A=1+f$, where $1>f>0$ pins down the effectiveness of the campaign. Under the outlined structure, the quality parameter does not affect the price set. To see this I derive the optimum price, without any assumption on quality. The firm seeks to maximize:

$$\begin{aligned} &\max_{p} \langle py - wn \rangle \quad s.t. \\ &y = p^{-\varepsilon} A \left(\frac{\varepsilon}{\varepsilon - 1} \right)^{\varepsilon} \\ &y = n \end{aligned} \tag{1.2}$$

where $w=1$ indicates the wage rate, which I normalize to one. Substituting in labor and output the first order condition reads:

$$(1-\varepsilon)\, p^{-\varepsilon} A \left(\frac{\varepsilon}{\varepsilon - 1} \right)^{\varepsilon} + \varepsilon \cdot p^{-\varepsilon-1} A \left(\frac{\varepsilon}{\varepsilon - 1} \right)^{\varepsilon} = 0 \tag{1.3}$$

rearranging the terms the optimal price reads:

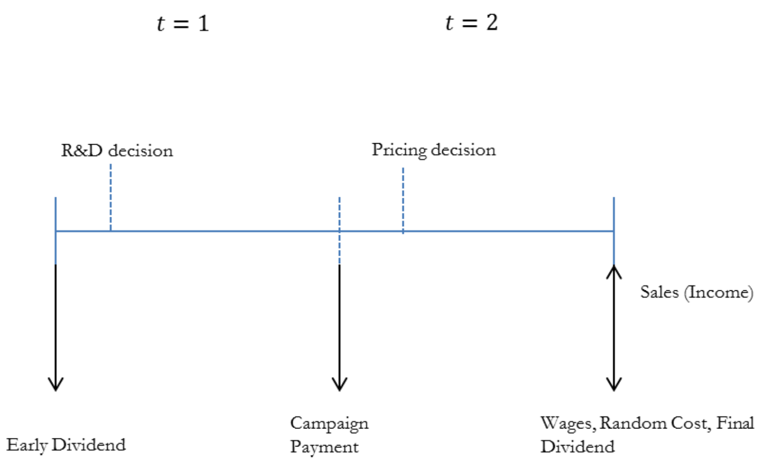
$$p^{*} = \frac{\varepsilon}{\varepsilon - 1} \equiv M \tag{1.4}$$

as it is standard in a CES framework. The optimal price, p^{*}, is set at a markup M over the wage rate, which is one by assumption. The price is independent of the amount of sales due to constant returns to scale. Therefore, an increase in quality simply allows for selling more output at the same optimal price. It is straightforward to see that equilibrium output is $y = A$ for all CES parameters, ε. As a useful notation the net markup is defined as $m=(M-1)$. For instance, a gross markup of 1.1 implies that the firm profits 10% over the cost, implying a net markup of 0.1.

b) The firms' problem

There are two subperiods for firms' decisions. In the first subperiod the following events take place. Firms start with a certain amount of cash that they can hold on to or distribute as dividends. Afterwards, a stochastic opportunity to launch an R&D campaign - with probability θ - arises. At that time, the firm decides whether or not to launch the campaign. At the end of the period, due to a cash-in-advance constraint, the firm has to pay for the campaign in the event that it has been launched. The cost of a campaign is γfm [5], with $\gamma < 1$, indicating that the cost is proportional to the gross profits it generates[6]. At the beginning of the second subperiod the pricing decision is made, after which the firm sells its output. At the end of the second period all payments except those for R&D campaigns are made, and all the resources available to the firm are distributed as a final dividend. Firms obtain revenue from their sales, can hold cash from each period to the next, and face as payments wages, R&D campaign costs and a random cost k. The random cost can take a positive value, $\bar{k}$, or a null value. The following timeline illustrates all payments and decisions.

Figure 1 – Timing of the problem



To ensure timely payments the supplier[7] (the agent that is entitled to receive payment of k) issues the (credible) threat of triggering the costly liquidation of the firm -which is assumed to cost all the cash held - if the cash held and the expected profits are not sufficient to cover the high realization of the cost. Thus the firm will be liquidated if there is a positive probability of not being able to pay what it owes, before the realization of the random cost is observed. This can be thought of as a shortcut of large bankruptcy costs that discourage any firm from choosing to file bankruptcy.
Finally, as firms start with an arbitrary sufficient level of cash, I assume that firms cannot borrow. They can however save cash and receive no interest. Nonetheless, to avoid firms holding cash simply because there is no opportunity cost associated with it, the late dividend is discounted with an impatience parameter $\alpha < 1$. This structure delivers the following maximization problem

$$\max_{d_1} \left\langle E_1 \left\{ d_1 + \max_{R\&D \in \{0,1\}} \left\langle \max_{p} \left\langle E_2 \left\{ \alpha d_2 \right\} \right\rangle \right\rangle \right\} \right\rangle \tag{1.5}$$

[5]Note that fm is the gross profit that the campaign generates; since f corresponds to the additional output sold (thanks to the campaign), and m is the net profit per unit sold.
[6]This result could be motivated by Nash bargaining, or maybe a surplus sharing scheme, with a union of R&D workers or a supplier of R&D services.
[7]The supplier could be the same workers within the firm, or an outside firm.

where d_1, is the dividend paid at the beginning of the period and d_2, the dividend paid at the end of the period[8]. $R\&D$, is a boolean variable that indicates whether a campaign has been launched. The restrictions are listed below. The fraction of the initial endowment saved is h_1, so the initial dividend is

$$d_1 = 1 - h_1 \tag{1.6}$$

Cash held at the beginning of the second period, follows

$$h_2 = h_1 - \gamma f\left(M - 1\right) \cdot R\&D \tag{1.7}$$

this law of motion simply reflects the payment of the R&D campaign, in the event that the campaign has been effectively launched. At any period cash held cannot be negative, thus $h_t > 0$. The late dividend, d_2, is subject to the resources available at the end of the period. Thus it is equal to cash held, revenue, minus wages and fixed cost, and the random cost:

$$d_2 = h_2 + py - y - k \tag{1.8}$$

Finally, costly liquidation[9] is triggered before the realization of the random cost k, if ex-ante the firm cannot guarantee being able to cover this cost. Therefore, if there is a positive probability of not being able to fulfill the payments, liquidation will take place and the dividend will be 0. Thus the final dividend is further restricted by

$$d_2 = 0 \; if \; h_2 + py - y - \bar{k} < 0 \tag{1.9}$$

It is important to highlight the following: k denotes the random cost, which can take a zero value or a high value $\bar{k}$. Thus, equation (1.8) is the general expression of resources left for distribution at the end of the period, whereas the inequality in (1.9) refers to the particular case of having a realization of a high cost.
Finally the quality parameter reads:

$$A = 1 + f \cdot R\&D \tag{1.10}$$

which reflects the fact that an R&D campaign, if launched, increases the quality.
Using the Bellman's principle of optimality each step of (1.5) can be solved separately by backward induction. I now analyze period by period the solution of each

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[8]In a dynamic model both dividends would be identically interpreted as distributed in the beginning of the period. Given that the present one is a static model, the early dividend is introduced to create a cost of opportunity of holding cash.
[9]The liquidation is assumed to stop all operations, and furthermore all cash held by the firm is lost in bankruptcy costs. This threat is later shown to ensure timely payments in equilibrium.

maximization step and find the value of the solution as a function of the state variables.

b.1) Period 2 - The pricing decision

The state variables previously determined are quality, A, and cash holdings, h_2. Additionally, firms face the demand and technology restrictions. Substituting (1.8) in $\max_p \langle E_2 \{\alpha d_2\}\rangle$ results in:

$$\max_{p(i)} \langle \alpha(h_2 + py - n) - \alpha E_2 \{k\} \rangle \quad s.t. \\ y = p^{-\varepsilon} A \left(\frac{\varepsilon}{\varepsilon - 1} \right)^{\varepsilon} ; y = n \tag{1.11}$$

where I have used the fact that the only random variable is the random cost. The first order condition is identical to section 2.1, and the price charged will be a constant markup over the wage rate: $p^* = \frac{\varepsilon}{\varepsilon - 1}$. I allow for heterogeneity in the price elasticity of demand. I assume the simplest form of heterogeneity. Some firms face a large elasticity consumer ε^l, and some a small one ε^s. This will result in some firms having a high markup $\overline{M} = \frac{\varepsilon^s}{\varepsilon^s - 1}$, and some a low one $\underline{M} = \frac{\varepsilon^l}{\varepsilon^l - 1}$.

I define these elasticities precisely below, as they depend on the random cost κ. Firms incur this cost. That with probability $1-\pi$ is $\underline{\kappa} = 0$ and that with probability π is:

$$\overline{k} = (A-1)m + \tau > 0 \tag{1.12}$$

where τ indicates the fixed component of the cost, and the variable component, $(A-1)m$, implies that the difference between profits and the high realization of the random cost is constant regardless of R&D campaigns. This feature greatly simplifies the analysis. The cost τ is a crucial parameter of the model, because I restrict the elasticities of substitution of high and low markup firms to be such that:

$$\underline{m} < \tau < \overline{m} \tag{1.13}$$

Henceforth, I will use interchangeably low (high) markup as low (high) profits firm. Substituting the optimal price, expression (1.9) becomes:

$$d_2 = 0 \; if \; h_2 < \tau - m \tag{1.14}$$

Note that firms with a high markup will never satisfy this condition, since cash holdings cannot be negative, $h_2 \geq 0$; and by construction $\tau < \overline{m}$. On the other hand firms with low markup may find the restriction binding if they are not carrying enough cash. In the appendix, the expected values of period 2 conditional on optimal behavior are summarized.

b.2) Late Period 1 - The campaign decision

During the 1st period the stochastic possibility of launching an R&D campaign arises. In particular with probability θ the firm is allowed to launch the campaign. In this case the firm will choose $R\&D$ such that it maximizes the value in period 1:

$$\max_{R\&D\in\{0,1\}} \langle V(A,h_2)\rangle \quad s.t. \\ h_2 = h_1 - \gamma f\left(M-1\right)\cdot R\&D \tag{1.15}$$

Conversely, with probability $1-\theta$ firms do not have the opportunity of launching a campaign, thus $R\&D=0$. When firms are allowed to take the decision, four different cases arise depending on the amount of cash held.

First, if a firm in period 1 is holding: $h_1 < \gamma fm$ the campaign cannot be afforded, therefore $R\&D=0$.

Second, if a firm has sufficient cash to pay for the campaign, but not enough as to guarantee that (1.9) does not hold, the firm will choose not to launch the campaign thus $R\&D=0$. This is, if a firm has a cash level below the following threshold[10]:

$$\gamma\, fm < h_1 < \gamma\, fm + \max\langle \tau - m, 0\rangle \tag{1.16}$$

carrying out the campaign would leave the next period cash low enough to trigger liquidation, delivering a value of zero. More succinctly: $h_2 < \tau - m \Rightarrow d_2 = 0 \Rightarrow V(A,h_2) = 0$. Therefore as long as the terminal value is positive, the firm will not carry out the campaign. This simply requires that the expected profit without launching the campaign, and thus with quality $A=1$, in addition to cash held is positive:

$$V(A=1,h_2) = \alpha\left[h_2 + m - \pi\tau\right] > 0 \tag{1.17}$$

This condition is always satisfied if one assumes an expected positive profit - a standard participation condition, as cash held cannot be negative, thus: $m > \pi\tau$ is assumed.

Third, there is the case in which sufficient funds are available to fund the campaign *and* avoid liquidation. This level of cash can be expressed as:

$$h_1 \geq \gamma\, fm + \max\langle \tau - m, 0\rangle \tag{1.18}$$

In this case, the terminal value of launching the campaign must be compared to not launching it. The decision will favor the campaign, $R\&D=1$, if $V(A=1+f, h_2 = h_1 - \gamma fm) > V(A=1, h_2 = h_1)$. Substituting appropriately this results in:

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[10]Note that in the case of a high markup firm $\tau < \overline{m}$, therefore the condition is identical to $h_1 < \gamma fm$ which straightforwardly results in the campaign not being launched.

$$1-\pi > \gamma \tag{1.19}$$

This condition simply ensures that the expected profit of the campaign is larger than its cost, and it is assumed to hold.

Fourth, and last, there is the case of not carrying enough funds to avoid liquidation. Such a level of cash $h_1 < \max\langle \tau - m, 0\rangle$, will always deliver a value of zero by definition, and an inability to launch the campaign $R\&D = 0$. I summarize in the appendix the decisions of this section, and their expected value.

b.3) Early Period 1 - The dividend decision

At the start of period 1 the firm decides how much early dividend it wants to distribute. Recall that initial cash is normalized to one, therefore the early dividend problem can be expressed as:

$$\max_{h_1} \langle 1 - h_1 + E_1 \{V(A, h_1)\}\rangle \tag{1.20}$$

$$s.to \; : \; h_1 \geq \underline{h} \tag{1.21}$$

where $\underline{h}$ indicates the lowest threshold of cash held for each value of $E_1\{V(A, h_1)\}$. The threshold can take the values $\underline{h} \geq 0$, $\underline{h} \geq \gamma fm + \max\langle \tau - m, 0\rangle$, $\underline{h} \geq \max\langle \tau - m, 0\rangle$. From the discussion above it can be inferred that the following structure can represent the expected value, $E_1\{V(A, h_1)\} = \alpha h_1 + \Omega$, where Ω indicates variables exogenous to h_1 *within the interval,* that is as long as $h_1 \geq \underline{h}$. Therefore I can find a first general solution by taking the FOC with respect to h_1, which reads:

$$-1 + \alpha < 0 \tag{1.22}$$

Since the change of the objective with respect to the control is strictly negative, the restriction must be satisfied with equality. Therefore, in general, a firm will hold $h_1 = \underline{h}$. This is intuitive, as firms earn no interest and are impatient they will only hold the minimum cash required to choose the desired solution.

With this solution the only step left to find optimal cash holdings is to compare cases and see which level of cash delivers the largest value of the objective function. The firm will only hold a positive amount of cash if the expected profit from holding that cash exceeds the impatience cost. The amounts of cash carried can only take exactly the threshold values, the expected value of each threshold is summarized in the table below. Up until now the discussion has been general, without taking into consideration whether the firm is a high profit or low profit firm, since the distinction was made implicitly using the expression $\max\langle \tau - m, 0\rangle$, which for high profit firms is simply zero. Now, given that a particular value of cash is of interest it is necessary to consider each case separately. The following table summarizes the information:

Cash Held, h_1	Expected Value $V_0 = 1 - h_1 + E_1\{V(A, h_1)\}$
High profit firm, $m = \overline{m}$	
0	$1 + \alpha[m - \pi\tau]$
$\gamma f m$	$1 - \gamma f m + \alpha[(1-\theta)\gamma f m + (1+\theta f)m - \pi(\theta f m + \tau)]$
Low profit firm, $m = \underline{m}$	
0	1
$\tau - m$	$1 - (\tau - m) + \alpha[\tau - m + m - \pi\tau]$
$\gamma f m + \tau - m$	$1 - (\gamma f m + \tau - m) + \alpha[\gamma f m + (\tau - m) - \theta\gamma f m + (1+\theta f)m - \pi(\theta f m + \tau)]$

It is evident that the condition for holding cash will vary depending on the markup of the firm. I first consider the simplest case -high profit firms. The decision is between not carrying any cash, and carrying just enough as to pay for the R&D campaign should the opportunity arise. The condition that must be satisfied to carry the cash reads:

$$\left[f\overline{m}\right]\alpha\left[(1-\theta)\gamma + \theta - \pi\theta\right] > \left[f\overline{m}\right]\gamma \tag{1.23}$$

where the term $\left[f\overline{m}\right]$ is not canceled for the purpose of illustration. The intuition is straightforward. On the right hand side, the reduction of the early dividend is found; on the left hand side, three discounted elements appear. First the expected value of cash carried by the end of the second period $\gamma\left[f\overline{m}\right]$ with probability $1-\theta$, then the expected profit of a campaign $\left[f\overline{m}\right]$ with probability θ, and finally the change in the random cost. The condition can be reduced to:

$$\left(1-\frac{1}{\alpha}\right)\gamma + \theta(1-\pi-\gamma) > 0 \tag{1.24}$$

The case of low profit firms is a little more convoluted. First there is a participation condition, operating must be more profitable than just simply distributing all the cash at the beginning. The participation condition reads:

$$\alpha[\underline{m} - \pi\tau] > (1-\alpha)(\tau - \underline{m}) \tag{1.25}$$

Note that in the previous section a laxer participation condition was obtained, $\underline{m} > \pi\tau$, due to the absence of discounting. This condition states that the discounted expected operations profit must exceed the opportunity cost of holding the cash. This condition ensures that a low profit firm holds enough cash to operate, and can be reduced to:

$$\underline{m} + \tau(\alpha - 1 - \alpha\pi) > 0 \tag{1.26}$$

For the firm to hold enough cash to operate and launch the campaign if presented with the opportunity another condition is required, in particular:

$$[f\,\underline{m}]\alpha\left[(1-\theta)\gamma+\theta-\pi\theta\right]>\gamma[f\,\underline{m}] \quad (1.27)$$

After canceling the term $[f\,\underline{m}]$ this condition is identical to (1.23) and thus conveys the same intuition. The reduced condition, therefore, will be the same as (1.24). If the conditions outlined are satisfied, which I assume they are, firms will hold cash as depicted in the following table:

High profit firm, $m=\overline{m}$	Low profit firm, $m=\underline{m}$
$h_1=\gamma f\,\overline{m}$	$h_1=\gamma f\,\underline{m}+\tau-\underline{m}$

Finally it is worth emphasizing that the conditions that make it optimal to carry cash for the campaign are independent of markup, and thus have no influence on the decision of whether to carry cash for the campaigns. Markups however do impose an important condition on low markup firms, the one that defines if they are willing to operate as opposed to simply distributing all cash as dividends at the beginning of the period.

c) Model predictions

From the theoretical model developed in the previous sections I infer two testable propositions. In the model, firms can be of two types, high markup and low markup. Low profitability firms face a probability of bankruptcy, whereas high profitability firms do not face this risk. The empirical predictions of the model are synthesized in the following three propositions.

Proposition 1 *Higher markup for high markup firms will lead ceteris paribus to higher cash holdings.*

Proof *High profitability firms,* $m=\overline{m}$ *, hold* $h_1=\gamma f\,\overline{m}$ *, ceteris paribus* $\frac{\partial h_1}{\partial \overline{m}}=\gamma f>0$.

Proposition 2 *Higher markup for low markup firms will lead ceteris paribus to lower cash holdings.*

Proof *Low profitability firms,* $m=\underline{m}$ *, hold* $h_1=\gamma f\,\underline{m}+\tau-\underline{m}$ *. Thus ceteris paribus,* $\frac{\partial h_1}{\partial \underline{m}}=(\gamma f-1)<0$ *. Since* $\gamma f<1$ *by construction*[11].

For the high markup firms the intuition is straightforward. They carry cash to cover the cost of the campaign, as the cost is assumed to be proportional to the potential profits of the campaign, and the potential profit according to the model outlined above is proportional to markup, it follows that cash is proportional to markup. The case of low markup firms is somewhat different. They carry the cost of the campaign as well, but additionally they hold cash to pay for a high realization of the random cost. In this case, as before an increase in the markup will cause the firm to carry more cash to pay for the

[11]Note that this result relies on the assumption that $f<1$, and thus $\gamma f<1$, in this framework there is no natural bound to how large the effectiveness of the campaign can be. If one wants to extend the R&D framework to a Dixit-Stiglitz model such a bound would be achieved. Nevertheless the main message is that firms with low profitability have a lower slope of cash holdings with respect to markup. Whether this difference is enough to turn the result negative is ultimately an empirical question.

campaign. However, it will also decrease the amount necessary to pay for the random cost, decreasing cash holdings overall. Furthermore the effects of markup on cash holdings are related to the firm level markup and not the industry one. Finally it is worth stressing that the relationship is contemporaneous. Firms' incentives to hold cash depend only on present values of markup, and not on past values. As it is explicit in expression (1.5), the cash holding decisions are forward looking in the sense that firms hold cash by taking into consideration what is going to happen during the period.

1.4 Data and Methodology

The models' propositions can be formulated as testable hypotheses:

First - following proposition 1- firms that have a sufficiently high markup, $\overline{m}$, do not require cash to avoid bankruptcy following the realization of the positive random cost, $\overline{\kappa}$. These firms only hold cash for strategic reasons. Therefore, as markup increases, the value of a campaign raises and firms respond by holding more cash.

HYPOTHESIS 1 *Cash holdings increase with markup if a firm has a sufficiently high markup*.

Second- following proposition 2- firms that have a sufficiently low markup ($\underline{m}$) require cash to avoid bankruptcy following the realization of the positive random cost ($\overline{\kappa}$). These firms hold cash both for precautionary and strategic reasons. Facing an increase in markup there are two opposite effects. The value of campaigns increases, but the amount of cash required to avoid bankruptcy decreases. The latter effect dominates the firms' decisions, so that firms hold less cash following an increase in markup.

HYPOTHESIS 2 *Cash holdings decrease with markup if a firm has a sufficiently low markup*.

According to the model, one would expect the estimation of the effect of markup on cash holdings to be positive for high markup firms, and the reverse for low markup firms. These hypotheses make it possible to differentiate between the strategic motive and the precautionary motive for holding cash within the scope of the markup effects on cash holding.

To test the model I will use measures of markup, and, at the same time, I will use an alternative measure of competitive pressure. The reason is that one of the main purposes of the study is to explain the diversity of results found in the literature. Thus, it is important to clarify the effect of different dimensions of competition. Additionally, the mechanism that produces the sign inversion of the effect is only related to profitability[12]. Therefore, I postulate a very general corollary with respect to competition dimensions outside of markup.

COROLLARY 1: *Competition dimensions outside of profitability are not predicted to present an inversion of the sign of the effect.*

[12]In my model the driver of profitability is markup, although many other factors may affect profit rates.

a) Markup and other competition measures

In order to perform the analysis I require a proxy for markup, m. The proxy for markup I use is the PCM, which is obtained by dividing operating income before depreciation by sales. This specification assumes that marginal and average costs are equivalent. The measure is obtained in the same manner as by Morellec, Nikolov and Zucchi (2013). When the aim is to replicate the result of these authors I use what MNZ label the excess price cost margin which is the firm price cost margin minus the industry price cost margin. The price cost margin is widely used in the literature - for instance see Epifani and Gancia (2011) or Tybout (2003)- and measures the capacity of a firm to price above costs, so providing a good approximation to markup. It is also a measure of the profitability rate (before taxes and interest). I use the PCM since I do not have access to prices and marginal costs data.

In the case of a proxy for competition in dimensions other than markup I use the product market fluidity index developed by Hoberg, Phillips and Prabhala (2012), and also used by MNZ. The measure is available for the period 1997-2010. Although the HPP index is labeled by the authors as product market fluidity, they interpret it as a measure of competition threats as well. Indeed the index measures competition intensity by the overlap of key words describing products of a firm and the changes in the aggregate usage of these words. The definition of the index is as follows, let n_t be the scalar equal to all key words used in product descriptions in year t. For each firm a boolean vector j_t of length n_t is used to describe its word usage. In particular, an element takes the value of 1 if the word is used and 0 if it is not used. To measure the aggregate change of word usage the vector $d_{t-1,t}$ is used, and is defined as

$$d_{t-1,t} \equiv \left| \sum_{\forall i} \left(j_{it} - j_{it-1} \right) \right| \tag{1.28}$$

where i indexes firms. The HPP index for each firm is the dot product between its own word vector and the normalized aggregate change vector

$$HPP_{i,t} \equiv \left\langle j_{i,t} \cdot \frac{d_{t-1,t}}{\left\| d_{t-1,t} \right\|} \right\rangle \tag{1.29}$$

To explain it with a simple example, let firm j have two key words describing its products in 2006, "android" and "smartphone". In the year 2005 let competitors of firm j have no product described by these key words. If in 2006 all of the competitors of firm j suddenly have as key words "android" and "smartphone" the HPP index will be 1. Alternatively if none of the competitors in 2006 have the key words, the index will be 0. Having described this measure, it is apparent that product market fluidity can a priori have strong effects on the elasticity of substitution, and so be highly correlated to PCM. I acknowledge this possibility, and precisely for this reason all the empirical analysis is carried out controlling simultaneously for the HPP index and the PCM. Moreover, product market fluidity is likely to capture another dimension of competition not related to markup. One crucial dimension in the literature about firm cash holdings and competition is the degree of potential threats from competitors[13]. For instance, this includes the capacity of a competitor to launch a campaign to acquire a firm's customers, or to develop a similar product, or even a strategic pricing campaign. I claim that product market fluidity is well suited to capture this dimension. Therefore the empirical strategy of adding both indicators in the regression aims to capture the effects of the profitability through the PCM variable, and the effects of competitive threats through the HPP index. This can only succeed if the measures do not present an excessive correlation. Fortunately this is not the case, as the R-squared in a simple OLS regression between the two measures is 0.005, which implies a correlation in absolute value of around 7%.

b) Sample

My sample is based on Compustat Industrial Annual files and the HPP database of product market fluidity for the period 1997-2010. The main limitation I face is that my sample appears to have substantially fewer available observations compared to MNZ[14]. Since one of the main empirical points of this study is to complement the results of the existing literature showing that both the precautionary and the strategic effects coexist, I first choose to replicate the results of Morellec, Nikolov and Zucchi (2013). I follow closely their empirical methodology with regard to both the creation of variables and treatment of the sample in order to demonstrate that the different results do not derive from having a different sample or differently defined variables.
Consistent with MNZ, I remove industries with SIC codes 4900 to 4999, regulated industries, 6000 to 6999, financial firms, and industries with the code ending in 0 or 9, which group firms with no well-defined industry. Further observations with missing SIC codes, total assets, cash and short term financial investments, sales and operating income are dropped. I also discard observations with negative or zero total assets or sales, and observations with a negative EBITDA larger than total assets. After these steps, I have available 26,975 firm year observations. I perform an additional step in which I drop 1,780 firm year observations for which the price cost margin (operating income before depreciation over sales) is extremely low. In particular, I drop the observations for which operating losses before depreciation are 100% the value of sales. The lowest value of operating income to sales in the sample is $-3 \cdot 10^6\%$.

c) Methodology

To test the three hypotheses I estimate by linear regression a model of cash holdings.

$$Cash_{i,t} = \beta_1 \underline{PCM}_{i,t} + \beta_2 \underline{HPP}_{i,t} + \beta' \underline{Controls}_{i,t} + \upsilon_t + \varepsilon_{i,t} \tag{1.30}$$

$$Cash_{i,t} = \beta_1 PCM_{i,t} + \beta_2 HPP_{i,t} + \beta' Controls_{i,t} + \phi_j + \upsilon_t + \varepsilon_{i,t} \tag{1.31}$$

[13]For instance, in the sense of the "monopolistic games" of Baskin (1987).

[14]The regression analysis carried out to perform a close exercise to MNZ delivers a sample 50% smaller.

where the underscore operator indicates deviation from the mean (and thus implies a firm fixed effect control), υ_t year fixed effects and φ_j industry fixed effects at the 4 digit SIC code level. In addition, I control simultaneously for markup, with its proxy the PCM, and other competition dimensions, with their proxy, the HPP index. In the control vector I add most of the controls used by MNZ. In particular, I include size, dividends, net working capital, capital expenditures, leverage, R&D expenditures and acquisitions; see Table 1 for precise definitions. The variable cash is the cash and cash equivalents to total assets ratio.

To test Hypothesis 1 and 2, I split the sample into two subsamples, one with high PCMs and one with low PCMs and run the regressions (1.30) (1.31) and compare the estimation of β_1 across samples.

Aside from the baseline models I complete several robustness exercises. To demonstrate that the results do not derive from having a different sample or different treatment of it, I replicate the results of MNZ and perform the same sample split. In this case I use the excess price cost margin (EPCM) as a proxy for markup, only include industry fixed effects (instead of firm fixed effects), and consider lagged values of the right hand side. The lag of markup is not relevant for the predictions of my model. However, if the competitive conditions are persistent enough lagged values can carry information about present values.

$$Cash_{i,t} = \beta_1 PCM_{i,t-1} + \beta_2 HPP_{i,t-1} + \beta' Controls_{i,t-1} + \phi_j + \upsilon_t + \varepsilon_{i,t} \qquad (1.32)$$

Other issues can arise regarding the baseline models. First of all, the sample split is made at a firm year level, and to ensure that no sample bias is supporting the results I consider a different sample split. Another problem that the model might have is that the strategic effect might be driven by a mechanic effect, as during profitable periods firms just accumulate more cash because they do not allocate it quickly enough. This effect can be aggravated by using firm fixed effects. This issue is not likely to alter the result since I control contemporaneously for cash flow. In addition, I also perform a firm fixed effect regression by smoothing the PCM with the HP filter and by pooling several years together, to ensure that short run variations do not drive exclusively the results. Finally I use a non parametric model to show how the precautionary and strategic cash holdings vary across profitability.

1.5 Results and Discussion

In this section I present and discuss the results obtained. First I discuss the results of replicating the MNZ study, then I consider the baseline models and finally I perform the robustness tests.

a) Consistency with Morellec, Nikolov and Zucchi (2013) and the coexistence of the strategic and precautionary motives

Since the main objective of this chapter is to show that precautionary and strategic cash holdings coexist, so complementing the literature that stresses the precautionary motive, for instance MNZ, and bearing in mind that I have access to a smaller sample than the one they use, it is crucial to be able to qualitatively replicate their results, at least as far as the key dimensions are concerned. Fortunately, the results are qualitatively close to MNZ. Table 2 presents them, in the third column the results obtained by MNZ are reported, whilst in the fourth the results of running the expression (1.32) are shown. The exercise performed is not exactly the same, since I do not use some of the controls the authors include, and because the exercise of controlling simultaneously for EPCM and the HPP index is not carried out by the authors. Nonetheless, the outputs are quite similar. Perhaps the most extreme change is the estimated coefficient for R&D which in my sample is reduced to a third of the value it had in MNZ. In the crucial dimensions of markup and other competitive pressures, and thus the estimated coefficients for the EPCM and the HPP index, no qualitative change is observed. Overall, this suggests that using a poorer sample than the one of MNZ and controlling for markup and another competition measure at the same time do not present a threat to the conclusions of this study. However, a substantial difference can be observed in the first and second columns where two subsamples according to profitability are used. I take the threshold of low profitability at a PCM of 0.05. Firm year observations[15] below this threshold comprise approximately 27% of the sample. Unreported robustness tests using other thresholds (as low as -0.05 at the 11th percentile or as high as 0.15 at the 64th percentile) show similar outputs. In column 1 results using the low profitability subsample are reported and column 2 reports the results of the high profitability sample. Hypothesis 1, that markup increases cash holdings for high profitability firms, is corroborated. The estimated coefficient of the PCM is 0.16 and significant at the 1% level. Hypothesis 2, that markup decreases cash holdings for low profitability firms, can be observed in column 1, where the estimated coefficient of the PCM is -0.19, and significant at the 1% level as well. Thus the precautionary and strategic motives of cash holdings appear to coexist. Nevertheless, using the whole sample the precautionary effect dominates the sign obtained on the coefficient of the PCM. In line with Corollary 1, the effect of competition outside of markup presents a different dynamic. In particular, it is found to be always positive, more competition leading to more cash held. The coefficients estimated for the non-markup competition proxy, the HPP index, are 0.012 and 0.006 respectively, both significant at the 1% level.

b) The strategic and precautionary effect of markup

In this section I want to prove that Hypotheses 1 and 2 are also consistent with the empirical evidence when using the models described in the expressions (1.30) and (1.31). To this end I perform a firm and an industry fixed effects regression on the two subsamples, one which includes high profitability firms and the other with low profitability firms. I take again the threshold of low profitability at a PCM of 0.05. Table 3 reports the results of the firm fixed effects regressions carried out on each of the subsamples and on the whole sample for comparison. The whole sample analysis is

[15]The use of firm year observations might raise concerns regarding endogeneity in sample selection. In the robustness section I consider alternative sample selection mechanisms and the results hold.

reported in Column 3. The most important changes with respect to the analysis of the previous section are the sign inversion of the coefficient of R&D which is now negative, the significance at the 1% level of dividends that were not significant before, and finally that PCM is not significant anymore while the HPP index is only significant at the 5% level. Column 1 reports the results of the subsample with firm-year observations of the PCM below 0.05. The coefficients associated with the controls do not change qualitatively with respect to the whole sample analysis except for the coefficient of cash flow that is three times larger and significant at the 1% level. Importantly, the proxy of competition outside markup, the HPP index, is no longer significant. The most important result is that the PCM has a large negative coefficient of -0.16, and is significant at the 1% level consistent with Hypothesis 2, and thus consistent with the precautionary motive for holding cash. In Column 2 the results of the high profitability sample are reported, and again some losses of significance can be observed for dividend, working capital, cash flow (which in addition switches signs[16]) and product market fluidity with respect to the whole sample result. However, the crucial result is the inversion of the sign of the PCM coefficient. From the reported -0.015 for the whole sample analysis, or from the -0.16 for the low profitability subsample, it now stands at 0.41 and is significant at the 1% level. This observation is consistent with Hypothesis 1. As a consequence I can infer that the coexistence of a precautionary motive that *decreases* cash holdings with higher markup or profitability, and a strategic motive that *increases* cash holdings with higher markup or profitability, is entirely consistent with the empirical evidence.

I now repeat the same exercise except that I use industry fixed effects instead of firm fixed effects. I follow the linear regression set up in (1.31). The results are reported in Table 4. The main differences between this exercise and the firm fixed effects exercise are the recovery of significance of the HPP index and the PCM for all samples used to the 1% level and the fact that R&D recovers the positive coefficient for the profitable firms subsample. The main point remains unaltered. An increase in markup for high profitability firms increases cash holdings and for low profitability firms decreases cash holdings. In addition the HPP index increases cash holdings in both subsamples. The coefficient of the PCM for high profitability firms is 0.23 and for low profitability firms is -0.32.

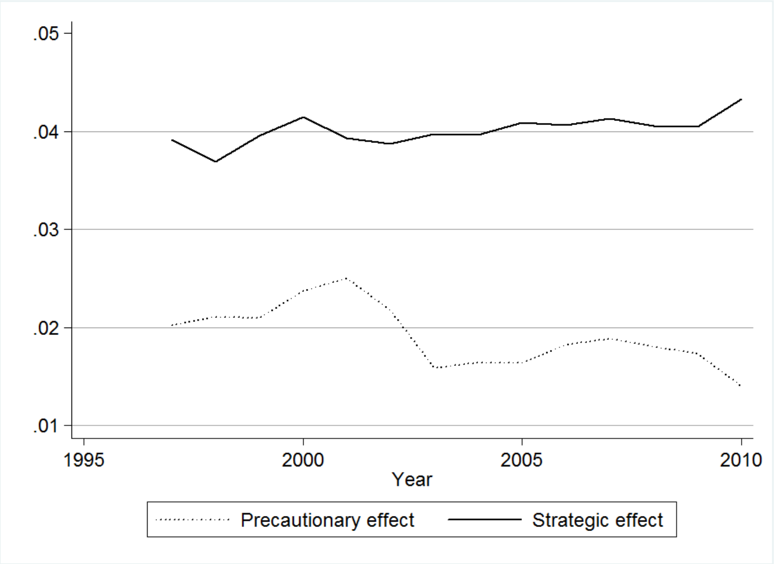
c) The dominance of the precautionary over the strategic motive

In all examined linear regression models the coefficient associated with the markup proxy using a whole sample analysis appears to suggest a dominance of the precautionary motive over the strategic one. I now present suggestive exercises regarding which of the effects is stronger both at the firm level and in aggregate. In the figure below I plot the average annual level effect (the average across firms of the product of estimated coefficient times the PCM for each subsample) of the strategic and the precautionary motive on the cash to assets ratio. The estimation result I use is the one from the industry fixed effects analysis described in expression (1.31). As can be observed the strategic effect dominates the precautionary one in the average effect per

[16]This can raise concerns that the results are driven by strong collinearity between cashflow and PCM. This is not the case, since if cashflow is left out, similar results are obtained.

firm.

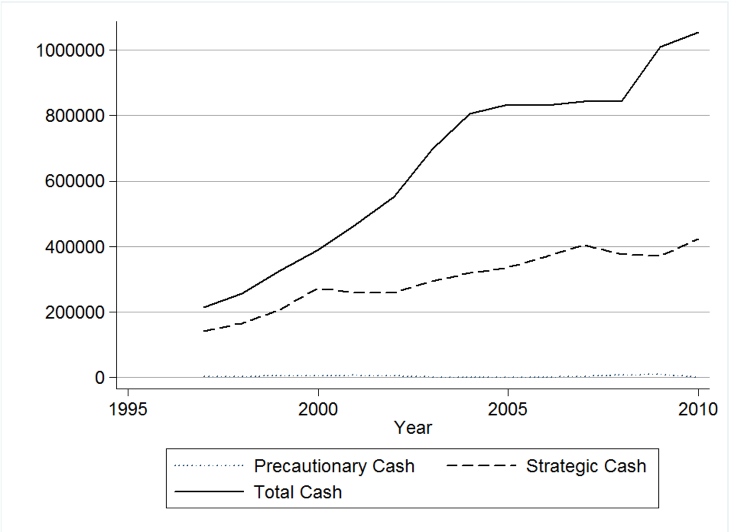
Figure 2 - The firm level precautionary and strategic effect



The plot is obtained by averaging the product of the estimated coefficient for the PCM and the PCM per subsample.

If one is interested in the overall cash held in aggregate by firms the figure above is not particularly useful. I now present a figure in which the effect of the strategic motive and the precautionary motive on the cash asset ratio is multiplied by asset level, and instead of being averaged is aggregated. I also plot total aggregate cash holdings. Thus, it can be interpreted as the aggregate effect of each motive on total cash level. As can be observed both the level and increase in cash holdings are on aggregate much stronger for strategic reasons than precautionary ones, and more than would be expected from the sample size relation, which is approximately 3:1. Even if in the regression analysis the effect of the precautionary motive appears to dominate the strategic one, in analyzing the two subsamples this dominance does not translate to aggregate data. In fact the average ratio between precautionary and strategic cash is approximately 1 to 115.

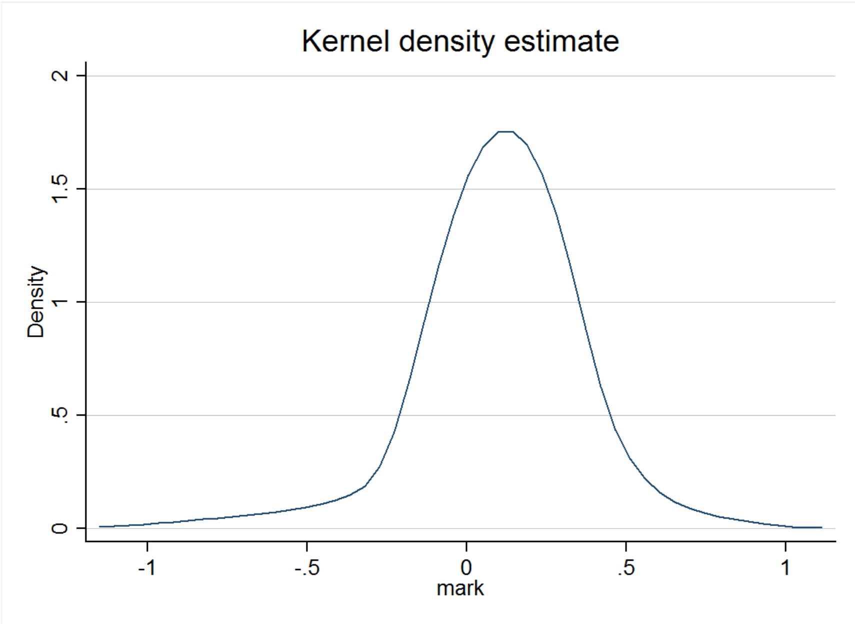
Figure 3 - The aggregate precautionary and strategic effect



The plot is obtained following the same methodology as above, but multiplying the result by asset level and aggregating all firms.

Elucidating the mechanism by which the precautionary motive appears to dominate in regression analysis is beyond the scope of this study. I can, however, plot a suggestive figure that presents a hint as to why this might be the case. The PCM appears to have a fat left tail. Since high observations of the PCM rapidly decay, whereas low observations of the PCM decay much more slowly, the overall fit favors a negative slope, pointing to the precautionary motive, instead of the strategic one.

Figure 4 - Density estimate of the PCM



d) Robustness exercises: subsample endogeneity, result stability, and contemporaneous timing and firm fixed effects.

The first robustness exercise concerns subsample selection bias. In the previous exercises I have used the firm year PCM to split the sample. I have done so because it represents the most appropriate way to test my model hypothesis. In the theoretical model, if a firm has a low markup during one period and a high one later on, the precautionary motive will dominate in the earlier one whilst the strategic motive will dominate in the later. However, the concern of endogeneity in sample selection is still valid and needs to be addressed. One way is to split the sample according to average profitability. But it is not a good method. This is because even if a firm has a high profitability on average, it can still have a bad year and if the PCM for that year is extremely low the results will be dominated by the precautionary motive as explained in the previous section[17]. A good alternative is to split the sample in the following manner. I choose as the high profitability subset the firms that in all periods have had a PCM

[17]Even if shocks are transitory, they can have the same effect. Only in the case of unpredicted shocks (by the firm) would they not have this effect.

over 0.05; these firms account for 10143 firm year observations. The low profitability sample is comprised of firms that have an average PCM between -1 and 0.05, and accounts for 7129 firm year observations. Firms that have an average PCM below -1 are simply discarded[18]. Table 5 reports the results of the exercise using the industry fixed effects regression model. The results are not qualitatively different in the crucial aspects from the analysis in the previous section[19], except for the coefficient of the PCM for the low profitability sample, which falls to -0.09. This is not very surprising given that in the subsample approximately 30% of firm year observations have a PCM higher than 0.05[20]. Nonetheless, the main objective of the exercise is to show robustness against possible sample selection bias for the high profitability firms[21], and it is successful since the coefficient associated with the PCM is qualitatively unaltered for the high profitability sample. In particular, the coefficient is 0.23 and significant at the 1% level. In an unreported exercise I repeat the same steps, but using firm fixed effects. The crucial results are quite similar, but the coefficient of the PCM for the low profitability sample is only significant at the 5% level. As I have just argued, this is of no importance since the focus of the exercise is on the high profitability sample.

The second robustness exercise concerns the stability of the result. To this end I perform a semiparametric exercise using the Stata routine lypoly. In a first step I run a regression of cash holdings on all the variables used throughout the analysis and industry fixed effects with the exception of the PCM. I also run a regression using the same independent variables as before, but in this case the dependent variable is the PCM itself, and store the residual. Finally, I find the semiparametric fit between the residuals of cash and the PCM. I repeat the same exercise with firm fixed effects. In the figure below the results are presented. For the industry fixed effects the sign shift is less stark than the one for fixed effects. In fact, if the bandwidth is reduced, the sign inversion takes place only at higher values of the PCM[22]. The Fixed Effects specification exhibits a clear sign inversion for the central values, whilst at the extremes the picture is not so clear. Nevertheless, as can be observed, this is the consequence of very few firm year observations.

[18]This subset of firms accounts for 1081 firm year observations, and are firms that on average have a Price Cost Margin below -100%.

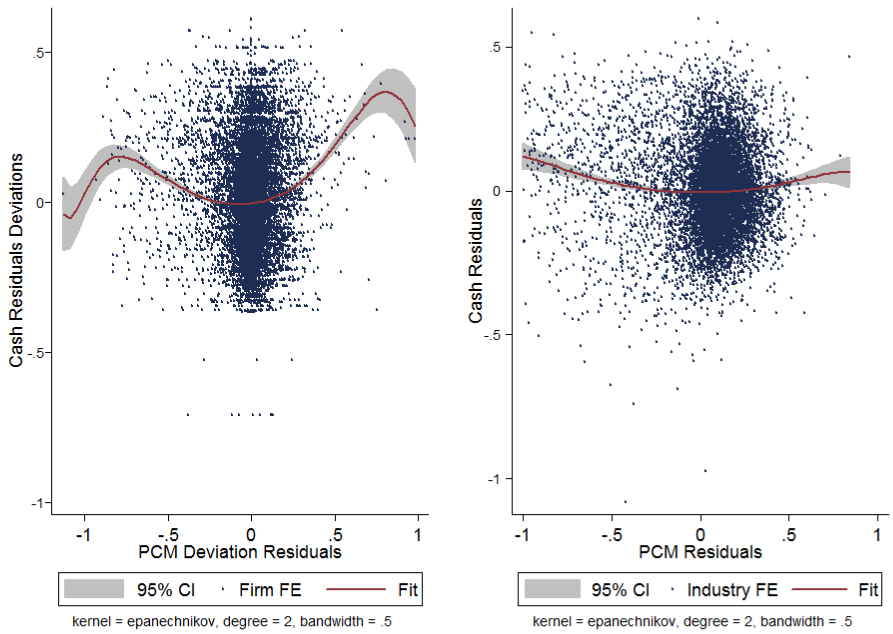
[19]If the mean PCM method is used and firms with an average PCM over 0.05 but some observations below -0.4 are discarded the results still hold. These firms account for only 432 firm year observations compared to a sample of 13350. It is plausible to assume that such large drops in profitability are at least partly anticipated by the firm.

[20]In fact if one selects the low profitability subsample selecting the firms that have in all years a PCM bellow 0.05 the original results are recovered, and the coefficient on PCM stands at -0.17.

[21]This is because it is precisely in the high profitability subsample that the result is different from the whole sample analysis.

[22]In an unreported exercise I run the industry fixed effects usual regression on the high profitability sample, discarding high values of PCM at several thresholds. The main results remain unchanged.

Figure 5 - Non parametric fit of Cash and the PCM



The exercise entails obtaining the residual of the regression for both variables, with firm or industry FE, and fitting the non parametric line after accounting for the controls.

Using firm fixed effects can be very useful if there is individual heterogeneity. If the unobserved heterogeneity is unrelated to the regressors then the Random Effects model is more efficient than the Fixed Effects model, an extensive discussion can be found in Greene (2008). The issue of which model to use OLS, RE or FE can be answered by statistical tests. As a first step, I use a Breusch Pagan (1980) test to establish whether the use of RE is preferable to OLS (in both models I include industry fixed effects). The test rejects the null hypothesis, at any usual significance level, of no firm heterogeneity and thus OLS is not an adequate choice. I then use a Hausman (1978) test to see whether the RE model can be used or whether one must use a FE model. The test rejects the null hypothesis that the difference between RE estimates and FE estimates is not systematic, at any usual significance level, and so I conclude that FE is the best-suited model for my sample.

Even if the firm fixed effects model is the most adequate for the analysis, a suspicion may arise that instead of estimating the strategic motive, I have just found a mechanical relationship between income and cash holdings. That is, the strategic motive implies a positive relationship between markup and cash held. Nonetheless, the proxy of markup, the PCM, has operating income in the numerator. If firms are inertial in the management of cash, the positive contemporaneous relationship between the PCM and cash holdings may derive from high income and not from markup. I argue that this is not the case, since I control contemporaneously for cash flow, which also includes operating income in the numerator. Moreover, as an additional robustness check I ensure that results are not driven by this effect. I perform the same exercise as in Table 3, a firm fixed effects regression across two subsamples, but now I smooth the PCM. In particular, I use the trend component of the PCM after applying an HP filter. To do this, I only keep firms which have no missing observations of PCM for the whole sample period (1997-2010).

The main results - reported in Table 6 - remain unchanged. For the high profitability sample the coefficient of the PCM is positive, 0.29, and for the low profitability sample it is negative, -0.29; both are significant at the 1% level. Another exercise with regard to the same issue is to pool firm year observations across years. In particular I transform the 14 year sample to a sample with 4 periods by aggregating variables across these periods. Using this transformed sample I run the same exercise as above. The results are reported in Table 7. As can be seen, they do not qualitatively differ from the ones reported above.

1.6 Conclusion

In the US there has been a long-term upward trend in firm cash holdings as a percentage of total assets. This increase is potentially worrying because it may shift resources from more productive assets to cash. Parallel to this trend, trade openness and import penetration have substantially increased – while evidence on markup measures is less clear. This has aroused interest in product market competition as an element in explaining the rise in cash holdings. Meanwhile, the literature has identified two main motives for firm cash holding. The first is the precautionary motive. Firms hold cash to cope with adverse shocks, such as operating losses or unexpected costs, and to avoid recourse to more costly external finance funds or costly liquidation. The second motive is the strategic motive, usually associated with the deep pocket argument. In this case, a firm holds cash to reduce competition. Thus a coexistence of both motives appears plausible. Nonetheless, in the cash and product market competition literature both model predictions and empirical results deliver contradictory results regarding the relationship of cash and competition. The generally labeled precautionary effect predicts a positive relationship between cash holdings and product market competition, whereas the strategic motive generally predicts a negative relationship between cash holdings and competition.

To understand the opposite effects on cash holdings that the strategic motive and the precautionary motive can have, I seek to establish with markup or profit rate measures whether the two motives can coexist and, if so, which one is most likely to dominate the overall effect. To this end, I develop a highly stylized partial equilibrium framework. In this model, firms can be of high or low markup. In addition, firms can launch R&D campaigns to temporarily boost product quality and face a positive probability of incurring a random cost, which can bankrupt low markup firms. Thus both strategic cash holding, to pay for the R&D campaign, and precautionary cash holding, to pay for the random cost and avoid bankruptcy, are present in the model. The main results are as follows. First, both types of firms hold cash for strategic motives, but only precautionary firms hold precautionary cash. Second, when both motives are present, the precautionary dominates the strategic. Third, precautionary cash decreases with markup as higher revenue lowers the need to save cash to pay for the random cost. Fourth, strategic cash increases with markup.

I next turn to an empirical exercise to analyze whether the model's conclusions hold, and crucially to test whether the low markup firms will respond to markup increases by decreasing cash holdings and the high markup firms by increasing cash holdings. Using Compustat firm level data, I estimate several regressions. The estimation results are consistent with the model. The effect of the proxy of markup depends on the PCM of the firm, in the manner predicted by the model. Interestingly, results using the whole sample indicate that the precautionary motive dominates. However, when the effect is estimated splitting the sample according to high and low profitability the strategic motive accounts for most of the cash held. Therefore, using the whole sample to assess the question can be highly misleading.

1.7 Appendix I - Data and empirical results

Table 1: DEFINITION OF VARIABLES

Variable	Variable Definition
Cash	Cash and Equivalents (CHE)/ Asset Total (AT)
PCM	Operating Income Before Depreciation (OIDP)/Sales (SALE)
HPP index	Hoberg,Phillips and Prabhala index
Size	log(Sales(SALE))
Dividend	Equal to 1 if Common Dividend (DVC) reported
Market to book	(Market value (CSHO * PRCC) + Book debt)/Asset Total
Cash flow	(EBITDA-Interest(INTPN)-Tax(TXT)-(DVC))/Asset Total
Working Capital	(Working Capital(WCAP)-Cash)/Asset Total
Capex	Capital Expenditures (CAPX)/Asset Total (AT)
Leverage	Book Debt/(Assets Total (AT) - Book equity+Market value)
R&D	R&D expenses (XRD)/Assets Total (AT)
Acquisitions	Acquisitions (AQC)/Assets Total (AT)
Book Debt	Long term debt (DLTT) + Debt in current liabilities (DLC)
Book Equity	Assets total (AT) - Book debt

Table 2: SAMPLE SPLIT USING THE NMZ METHODOLOGY

Table 2 Reports the result of splitting the sample into two subsamples. The subsamples correspond to high profitability (PCM>0.05) and low profitability (PCM<0.05) firm-year observation. The sample is based on Compustat over the period 1997-2010. The symbols *,** and *** indicate significance level at the 1%, 5% and 10% levels respectively. The significance level is obtained using clustered robust standard errors. The coefficient reported for EPCM in column 3 is in parenthesis because it has not been obtained from the same regression as the rest of the exercises. It is added for the sake of comparability and in fact is obtained from a sample of 67123 firm-year observations and without controlling for the HPP index. Regressors enter in the regression lagged.

Dependent var: Cash Regressors (t-1)	Low sample (1)	High sample (2)	MNZ results (3)	Whole sample (4)
EPCM	-0.185***	0.157***	(-0.055***)	-0.076***
HPP index	0.012***	0.006***	0.011***	0.009***
Size	-0.005	-0.027***	-0.017***	-0.022***
Dividend	0.015	-0.008	-0.006*	-0.004
Market to book value	0.004**	0.008***	0.012***	0.007***
Cash flow	0.183***	-0.119**	0.029***	0.083***
Working Capital	-0.228***	-0.291***	-0.231***	-0.282***
Capex	-0.363***	-0.598***	-0.580***	-0.540***
Leverage	-0.423***	-0.357***	-0.249***	-0.383***
R&D	0.14***	0.348***	0.467***	0.164***
Acquisitions	-0.156***	-0.281***	-0.369***	-0.246***
Year Fixed Effects	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes
Observations	3266	7488	21461	10754
Adjusted R^2	0.50	0.54	0.54	0.52

Table 3: TESTING THE COEXISTENCE OF THE PRECAUTIONARY AND STRATEGIC MOTIVE-FIRM FIXED EFFECTS

In Table 3 the results of the analysis performed on two subsamples are reported. The subsamples correspond to high profitability (PCM>0.05) and low profitability (PCM<0.05) firm-year observation. The sample is based on Compustat over the period 1997-2010. The symbols *,** and *** indicate significance level at the 1%, 5% and 10% levels respectively. The significance level is obtained using clustered robust standard errors. Regressors enter in the linear regression contemporaneously.

Dependent var: Cash Regressors (t)	Low sample (1)	High sample (2)	Whole sample (3)
Competition: PCM	-0.156***	0.410***	-0.013
Competition: Fluidity	0.001	0.002*	0.002**
Size	-0.063***	-0.067***	-0.061***
Dividend	0.035**	0.006	0.027***
Market to book value	0.005***	0.004***	0.006***
Cash flow	0.201***	-0.085**	0.072*
Net working capital	-0.150***	-0.323**	-0.241***
Capex	-0.271***	-0.364***	-0.320***
Leverage	-0.211***	-0.189***	-0.230***
R&D	-0.225***	-0.150*	-0.270***
Acquisitions	-0.178***	-0.261***	-0.234***
Year Fixed Effects	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes
Observations	3829	8404	12233
Within R^2	0.19	0.24	0.19

Table 4: TESTING THE COEXISTENCE OF THE PRECAUTIONARY AND STRATEGIC MOTIVE- INDUSTRY FIXED EFFECTS

In Table 4 the results of the analysis performed on two subsamples are reported. The subsamples correspond to high profitability (PCM>0.05) and low profitability (PCM<0.05) firm-year observation. The sample is based on Compustat over the period 1997-2010. The symbols *,** and *** indicate significance level at the 1%, 5% and 10% levels respectively. The significance level is obtained using clustered robust standard errors. Regressors enter in the linear regression contemporaneously.

Dependent var: Cash Regressors (t)	Low sample (1)	High sample (2)	Whole sample (3)
Competition: PCM	-0.328***	0.234***	-0.121***
Competition: Fluidity	0.011***	0.006***	0.010***
Size	-0.013***	-0.032***	-0.026***
Dividend	0.020	-0.010	-0.001
Market to book value	0.007***	0.011***	0.009***
Cash flow	0.373***	-0.170***	0.129***
Net working capital	-0.306***	-0.386***	-0.368***
Capex	-0.460***	-0.665***	-0.612***
Leverage	-0.440***	-0.386***	-0.420***
R&D	0.021	0.247***	-0.007
Acquisitions	-0.182***	-0.349***	-0.287***
Year Fixed Effects	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes
Observations	4544	8404	12233
Within R^2	0.60	0.59	0.56

Table 5: ROBUSTNESS, ALTERNATIYE SAMPLE SPLIT

In Table 5 the results of the analysis performed on two subsamples are reported. The subsamples correspond to high profitability firms, PCM>0.05 in every period, and low profitability firms, average PCM between -1 and 0.05. The sample is based on Compustat over the period 1997-2010. The symbols *,** and *** indicate significance level at the 1%, 5% and 10% levels respectively. The significance level is obtained using clustered robust standard errors. Regressors enter in the linear regression contemporaneously.

Dependent var: Cash Regressors (t)	Low sample (1)	High sample (2)	Whole sample (3)
Competition: PCM	-0.094***	0.228***	-0.072***
Competition: Fluidity	0.012***	0.005**	0.009***
Size	-0.011**	-0.030***	-0.026***
Dividend	0.034*	-0.007	-0.002
Market to book value	0.007***	0.009***	0.010***
Cash flow	0.121***	-0.122	0.066**
Net working capital	-0.335***	-0.336***	-0.355***
Capex	-0.561***	-0.601***	-0.592***
Leverage	-0.596***	-0.332***	-0.432***
R&D	-0.061	0.232**	-0.012
Acquisitions	-0.222***	-0.276***	-0.283***
Year Fixed Effects	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes
Observations	4002	4281	11958
R^2	0.50	0.59	0.55

Table 6: ROBUSTNESS, DISCARDING SHORT TERM FLUCTUATIONS

In Table 6 the results of the analysis performed on two subsamples are reported. The subsamples correspond to high profitability firms, smooth(PCM)>0.05, and low profitability firms, smooth(PCM)<0.05. The sample is based on Compustat over the period 1997-2010. Smooth(x) indicates the trend component of variable x, the trend is obtained using the HP filter. The symbols *,** and *** indicate significance level at the 1%, 5% and 10% levels respectively. The significance level is obtained using clustered robust standard errors. Regressors enter in the linear regression contemporaneously.

Dependent var: Cash Regressors (t)	Low sample (1)	High sample (2)	Whole sample (3)
Competition: smooth(PCM)	-0.291***	0.288***	0.012
Competition: Fluidity	-0.000	0.001	0.001
Size	-0.040***	-0.054***	-0.049***
Dividend	0.034	0.013**	0.026***
Market to book value	0.002	0.006**	0.006***
Cash flow	0.170***	-0.010	0.113***
Net working capital	-0.206***	-0.349***	-0.280***
Capex	0.001	-0.341***	-0.260***
Leverage	-0.195***	-0.202***	-0.223***
R&D	-0.315***	-0.229**	-0.321***
Acquisitions	-0.071	-0.193***	-0.171***
Year Fixed Effects	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes
Observations	987	4194	5181
Within R^2	0.21	0.25	0.22

Table 7: FIRM FIXED EFFECTS POOLING YEARS

In Table 7 the results of the analysis performed on two subsamples are reported. The subsamples correspond to high profitability mean(PCM)>0.05 and low profitability mean(PCM)<0.05 firm-period observation. There are 4 periods in the transformed subsample, respectively: 1997-2001, 2002-2004,2005-2007,2008-2010 The sample is based on Compustat over the period 1997-2010. The symbols *,** and *** indicate significance level at the 1%, 5% and 10% levels respectively. The significance level is obtained using clustered robust standard errors. Regressors enter in the linear regression contemporaneously.

Dependent var: Cash Regressors (t)	Low sample (1)	High sample (2)	Whole sample (3)
Competition: PCM	-0.224***	0.355***	-0.048
Competition: Fluidity	0.001	0.001**	0.001*
Size	-0.056***	-0.063***	-0.058***
Dividend	0.003	0.005	0.013*
Market to book value	0.002	0.002***	0.002***
Cash flow	0.273***	-0.170	0.112*
Net working capital	-0.090*	-0.304**	-0.237***
Capex	-0.230	-0.256***	-0.255***
Leverage	-0.218***	-0.257***	-0.259***
R&D	-0.109	0.111	-0.164*
Acquisitions	-0.212	-0.187***	-0.191***
Year Fixed Effects	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes
Observations	1160	2573	3733
Within R^2	0.21	0.23	0.20

1.8 Appendix II - Model details

a) Details for section: Period 2 - The pricing decision

With the analysis carried out in section 1.3.b.1 the expected values of period 2 conditional on optimal behavior, $V = \max_{p(i)} \langle E_2 \{\alpha d_2\} \rangle$, can be found. A firm with the state variables relative quality, A, and cash holdings, h_2, has a terminal value of

$$V(A,h_2) = \alpha[h_2 + Am - \pi((A-1)m + \tau)] \; if \; h_2 \geq \tau - m$$
$$V(A,h_2) = 0 \; if \; h_2 < \tau - m$$

b) Details for section: Late Period 1 - The campaign decision

I summarize in the matrix below the results from section 1.3.b.2, according to the state variable cash held.

Cash Held, h_1	Decision	Value $V(A,h_1)$
With probability θ (The firm is allowed to launch the R&D campaign)		
$h_1 < \gamma fm + \max\langle \tau - m, 0 \rangle$	$R\&D = 0$	$\alpha[h_1 + m - \pi\tau]$
$h_1 \geq \gamma fm + \max\langle \tau - m, 0 \rangle$	$R\&D = 1$	$\alpha[h_1 - \gamma fm + (1+f)m - \pi(fm + \tau)]$
$h_1 < \max\langle \tau - m, 0 \rangle$	$R\&D = 0$	0
With probability $1-\theta$ (The firm is *not* allowed to launch the R&D campaign)		
$h_1 \geq \max\langle \tau - m, 0 \rangle$	$R\&D = 0$	$\alpha[h_1 + m - \pi\tau]$
$h_1 < \max\langle \tau - m, 0 \rangle$	$R\&D = 0$	0

Since the firm does not know in advance whether or not it will be allowed to launch the campaign the expected value is of interest. The matrix below summarizes the information.

Cash Held, h_1	Expected Value $E_1\{V(A,h_1)\}$
$h_1 < \gamma fm + \max\langle \tau - m, 0 \rangle$	$\alpha[h_1 + m - \pi\tau]$
$h_1 \geq \gamma fm + \max\langle \tau - m, 0 \rangle$	$\alpha[h_1 - \theta\gamma fm + (1+\theta f)m - \pi(\theta fm + \tau)]$
$h_1 < \max\langle \tau - m, 0 \rangle$	0

2. Debt and productivity: Evidence from firm-level data[23]

2.1 Abstract

There are relatively few studies that use micro data to shed light on the relationship between finance and productivity growth – one of the few that exists shows that there is a positive relationship between debt and future productivity growth. Meanwhile, several new macro-econometric studies have shown that there is a threshold of financial development above which finance negatively impacts growth – this chapter contributes to this literature by examining whether this finding holds when we examine firm level data. Our data is a firm level panel based on FactSet. Our results are the following: i) firm level debt is positively associated (not always significantly) with productivity; ii) aggregate debt in a country has a negative effect on firm productivity, controlling for GDP and other aggregate factors. Furthermore, given the potential issue of reverse causality, we examine the impact of aggregate debt on the unexpected components of productivity – our results show that aggregate debt is negatively associated with the unexpected component of firm productivity, thus lessening the concerns. Finally, to shed light on the cause of the negative impact of aggregate debt on firm TFP, we find that real estate valuation – which from an accounting perspective can lower firm level TFP – is a likely cause of the observed phenomenon.

2.2 Introduction

There are relatively few studies that use micro data to shed light on the relationship between finance and productivity growth. A recent study by Levine and Warusawitharana (2014)[24] is among the exceptions as it uses firm level data – it shows that there is a positive relationship between debt and future productivity growth. Building on this work by LW (2014), our study goes further and examines whether there is a difference between the relation of firm level debt and firm level TFP, and aggregate debt and firm level TFP. Several new studies have shown that there is either a threshold of financial development (measured by private sector credit to GDP) above which finance negatively impacts growth of GDP or TFP, or a direct negative impact to TFP, (Cecchetti and Kharroubi, 2012; Arcand, Berkes and Panizza, 2011), we examine whether this finding holds when we examine firm level data. Furthermore, LW (2014) look only at the effect of firm level debt on firm level productivity, we examine the case of aggregate debt as well to see if their finding holds for aggregate debt.

The relation between finance and economic growth has been extensively explored theoretically; two excellent reviews are Levine (2005) and Levine (1997). The link between finance and productivity has often been considered in the more general scope of economic growth. As framed in Levine (1997) the relation is presented as follows. In a friction-less world, such as the Arrow Debreu model, the financial system has no role in improving economic growth. Once frictions exist, finance can – by alleviating their effects – improve economic growth via an increase of productivity, capital

[23] This chapter is based on a project developed for the ILO Research Department, which provided the data used. I acknowledge the co-author of the project and an homonymous article; Sameer Khatiwada.

[24] Hereafter referred to as LW (2014).

accumulation, or both. The manner in which finance can affect these factors are placed in the following taxonomy by Levine: facilitate the trading, hedging, diversifying, and pooling of risk; [better] allocate resources; monitor managers and exert corporate control; mobilize savings; and facilitate the exchange of goods and services. As an example of a contribution which considers the effect of finance directly on productivity, Greenwood and Smith (1997) present a model in which specialization increases productivity, and given that transactions are costly, financial development leads to lower transaction costs and hence higher productivity. In general, until recently, both theoretical and empirical studies pointed to a positive association between finance and productivity[25].

More recent studies have pointed to the negative relation between finance and productivity mainly from an empirical point of view, nonetheless plausible explanations have been modelled for instance: that the financial sector crowds out workers from other more productive sectors; Cecchetti and Kharroubi (2015). As mentioned above LW (2014) is an exception to the trend, the authors present a model in which productivity enhancing projects require investment, and part of it has to come from external sources – therefore increasing debt can increase productivity at the firm level.

There are many dimensions of financial development as highlighted by Sahay et al (2015), but a country's level of financial development is generally captured by the availability of credit in the economy. Most macro-econometric studies tend to look at private sector credit as a share of GDP as the indicator of financial development (for a small but representative sample of studies, see Cecchetti and Kharroubi, 2012; Arcand, Berkes and Panizza, 2011; King, Levine and Loayza, 2000). In this chapter we examine the relationship between debt and firm level productivity. This is in line with LW (2014); they use debt as a measure of finance.

The contribution of this study is to test two closely related hypotheses. First, we propose that it is necessary to distinguish debt at the firm and aggregate levels. From the theoretical models proposed in the literature it is evident that even if firms are identical ex-ante the effects of aggregate or firm level debt can easily differ. For instance, in LW the increase in debt for a firm will increase TFP for that particular firm, but at the same time others firms debt will not have any effect on that firm's productivity. Conversely, if the increase in debt leads to a more vulnerable financial-economic system the firm level debt has no effect on the productivity of a particular firm (or a negligible effect), but aggregate debt will have a negative impact. Our empirical results support the importance of the postulated hypothesis, we find indeed that: i) firm level debt is positively associated with TFP (the statistical significance of the result depends on the estimation procedure for TFP); ii) aggregate debt in a country has a statistically significant negative effect on TFP. The second result is notable because we not only replicate LW 2014 (by finding positive relationship between firm level debt and productivity), we find a negative relationship between aggregate debt and firm productivity, essentially bridging the gap between micro and recent macro-econometric studies. Therefore the first hypothesis is validated by our empirical analysis, when studying the relation between finance and productivity it is of crucial importance to consider the different effects at the unit or aggregate level.

Second, we propose as a second hypothesis the mechanism through which aggregate debt can have a negative effect on productivity and we test it. The hypothesis has two parts, the first is that debt and real estate prices at the aggregate level have a positive causal link, in either or both directions. The second is that aggregate real estate prices

[25] It is worth mentioning, as stressed by Levine, that in the decade of the 1990's and earlier, there was a certain tendency to ignore finance altogether from the study of economic and productivity growth.

(both sale price and rental) have ceteris paribus a negative impact on firm level productivity. The reason is almost an accounting identity, higher real estate prices in aggregate for a firm that remains with the same factor input and sales can have a negative effect on productivity by lowering value added (due to increased rental costs and thus lower operating income). Alternatively, a firm that acquires a new property at a higher nominal valuation than the firm's own existing real estate does not see an increase in value added proportional to the increase in the nominal real estate stock. We propose to test the second hypothesis directly in its two components. The empirical results are the following, when using a proxy of productivity robust to the property valuation effects the effects of aggregate debt on firm level productivity vanish, furthermore when introducing a proxy of nominal real estate stock at the country level the results vanish as well, finally focusing on countries and sectors with low usage of real estate results in the loss of the estimated negative relation. We claim that these constitute at least a valid first test of the postulated hypothesis.

Methodologically, this chapter uses a standard panel data model to assess the relationship between debt and productivity. In order to account for the persistence of TFP growth, we use dynamic panel data techniques commonly used in the literature.[26] Furthermore, we estimate TFP based on the Levinshon and Petrin method, to examine the effects of debt on the unexpected components of TFP uniquely.

The rest of the chapter is organized as follows: Section 3 provides a review of the literature that looks at the relationship between financial development and economic growth. Section 4 discusses the firm level data used. Section 5 presents the empirical methodology employed. Section 6 presents the main results.

2.3 Literature Review

a) Efficient allocation of resources and impetus for growth

Finance plays a pivotal role in the allocation of capital resources. The functioning of the financial system is vitally linked to economic growth and countries with larger banks and more active stock markets have grown faster even after controlling for other determinants of economic growth (Levine, 1997). Financial intermediaries provide access to economies of scale and they increase economic efficiency by reducing technological and incentive frictions (Becsi & Ping, 1997). They increase the "quality of aggregate investment by enhancing profitable opportunities" thus contributing to economic growth (Becsi & Ping, 1997). Channels through which financial development is linked to growth are: growth rate of physical capital and efficiency in the allocation of capital (King and Levine, 1993). Furthermore, cross-country evidence on the role of financial development is consistent with the Schumpeterian view: financial intermediaries affect economic development primarily by influencing total factor productivity (TFP) growth (Beck, Levine, and Loayza, 2000).

Industries and sectors that rely on external financing grow disproportionately faster in countries with well-developed financial sector. Indeed, Rajan and Zingales (1998) show that financial development leads to economic growth by reducing the cost of external

[26] For the development of dynamic methods see Arellano and Bover (1995) and Arellano & Bond (1997) and for the applications of such models to study the link between productivity and finance, see LW (2014).

finance to financially dependent firms. They show that financial development is particularly beneficial to new firms in an economy by lowering the barriers to entry. In other words, low levels of financial development favors incumbent firms. This view echoes the famous work on economic development by Schumpeter (1911), where he said that access to credit was the basis for innovation and creation of new enterprises.

The prevalent view among economists and policy makers was that financial development follows economic development (Robinson, 1952). This view suggests financial sector will develop to cope with the needs of the real economy. But, relatively recent literature suggests that there is a first order relationship between financial development and growth. In fact, financial development is a good predictor of future economic development (Levine, 1997). “Finance does not only follow growth; finance seems importantly to lead economic growth” (King and Levine, 1993). Levine (1997) argues that theory and evidence make it difficult to argue that financial system merely responds to industrialization and economic activity. He says that a well-functioning financial system acts as an important precursor to economic growth.

Indeed, studies that look at the financial and economic history of the world show that economic leadership grew out of a strong financial base following a “financial revolution” (Rousseau, 2002; Sylla, 2000). Among the main features of this “financial revolution” includes four key aspects: i) strong public finance; ii) stable money that serves as a useful medium of exchange; iii) banking system that accepts deposits of money and lends it to credit-worthy borrowers; and iv) a central bank that serves as the government’s bank and a regulator and supervisor of the financial system.

b) Financial development does not necessarily lead to growth

On the eve of the Great Recession in 2006, Rajan (2006) suggested that while financial development on the whole had provided much greater access to finance for firms and households, it had also increased the exposure to risks and rendered the real economy vulnerable to severe fluctuations. Rodrik and Subramanian (2009) show that financial development has not necessarily led to higher investment growth or GDP growth in emerging economies, in fact, it might have led to more volatility and exposure to risks and increased likelihood of financial crisis. So the evidence on the link between financial development and growth is far from settled. For example, Demetriades and Hussein (1996) find no evidence of financial development leading to growth. Meanwhile, Arestis, Demetriades and Luintel (2001) show that financial development measured as stock market capitalization ratio does not necessarily lead to growth. Also, they point out that stock market volatility negatively affects real economic activity. They also show that bank-based financial development is better than capital-market based ones.

Arcand, Berkes and Panizza (2011) have shown that there is a non-monotonic relationship between financial development and the authors show that their results are significant controlling for macroeconomic volatility, banking crises, and institutional quality. Their finding is similar to that of Easterly, Islam and Stiglitz (2000), who show that there is a non-monotonic relationship between financial depth and output volatility, particularly that volatility starts increasing when private credit as a share of GDP reaches 100 per cent. Similarly, Cecchetti and Kharroubi (2012) show that there is an inverted-U relationship between financial development and productivity growth – when private credit reaches a point where it exceeds GDP, it becomes a drag on productivity growth. Other studies that highlight the non-monotonic relationship between financial development and growth are Deidda and Fattouh (2002) and Rioja and Valev (2004).

Cecchetti and Kharroubi (2012) argue that the financial industry competes for human resources with the rest of the economy. In fact, they attract the best and the brightest away from other sectors of the economy. Cecchetti and Kharroubi (2012) show that when the share of employment in the financial industry exceeds 3.5 per cent total employment, further increases tends to be detrimental to growth. While subsidizing the financial sector can increase the investments that entrepreneurs can undertake, it can also decrease the number of entrepreneurs by attracting more individuals to the financial sector (Philippon, 2007). Baumol (1990), Murphy, Shleifer, & Vishny (1991), and Philippon (2007) argue that the flow of talented individuals into financial services is not socially desirable because the social returns are higher in other occupations, even though the private returns are not.

One of the ways to examine the usefulness of finance to firms is to look at financial innovation and its impact on firms and the broader economy. In the wake of the Great Recession, Paul Volcker, former chairman of the Federal Reserve, argued that the only socially useful financial innovation of the last few decades is the automatic teller machine (ATM).[27] While the verdict on the usefulness of financial innovation is not as damning as Volcker's assertion, recent studies have cast doubt on the usefulness of financial innovation, particularly underscoring their impact on financial fragility. Studies show that financial innovation doubled between the late 1990s and the late 2000s and most of these were in the structured market (securitization and derivatives). A cross-country study of financial innovation shows that countries where banks spend more on financial innovation, they are also more fragile (Beck, Chen, Lin and Song, 2012).

c) Finance and firm growth

While, the debate on whether financial development leads to growth is not settled, what is undoubtedly true is that financing plays an important role in the functioning and growth of small and medium sized enterprises (SMEs), defined as enterprises with up to 250 employees – they tend to constitute over 60 per cent of total employment in manufacturing in many countries (Ayyagari et al, 2007).[28] Beck and Demirguc-Kunt (2006) show that SMEs are financially more constrained than large firms, and thus face growth constraints. On average, the share of investment financed with bank loans for small firms is 15 per cent, while it is 22 and 28 per cent respectively for medium and large firms (Beck et al, 2004). Also, not surprisingly, larger firms finance a greater share of investments with equity than smaller firms. According to Beck et al (2005), higher financing obstacles faced by small firms translate into slower growth. They show that smallest firms are adversely affected by financial, legal, and corruption constraints; therefore, financial and institutional development helps to close the gap between small and large firms.

Indeed, industries and sectors that rely on external financing grow disproportionately faster in countries with well-developed financial sector. Indeed, Rajan and Zingales (1998) show that financial development leads to economic growth by reducing the cost of external finance to financially dependent firms. They show that financial development is particularly beneficial to new firms in an economy by lowering the

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[27] Accessed on May 28, 2013: http://online.wsj.com/article/SB10001424052748704825504574586330960597134.html

[28] For example, in Chile, Greece, and Thailand more than 80 per cent of the workforce is employed in SMEs (Ayyagari et al, 2007). SMEs contribution to both employment and GDP exhibits a strong positive correlation with GDP per capita.

barriers to entry. In other words, low levels of financial development favors incumbent firms. This view echoes the famous work on economic development by Schumpeter (1911), where he said that access to credit was the basis for innovation and creation of new enterprises.

While access to finance plays an important role in firm growth, depending on the nature and types of finance, it could also have a negative impact on firms. For e.g., Kalemli-Ozcan, Sorensen and Volosvych (2010) show that firms in the EU-15 with higher levels of foreign ownership are more volatile and changes in foreign ownership over time is positively associated with volatility.[29] In fact, if the largest owner of a firm is foreign, then sales growth of the firm is 20 per cent more volatile than the average in the sample. Furthermore, this micro-level effect translates into the macro level. The authors show that financial integration explains around 12 per cent of the variation in regional volatility. In order to establish causality, the authors use propensity matching to compare firms with no foreign ownership with the ones that have foreign ownership and are observationally similar – the result showing 'higher ownership associated with increased volatility' holds.

Meanwhile, Gennaioli, Shleifer and Vishny (2012) show that the securities that were created leading up to the Great Recession "neglected risks," which in turn were amplified by the excessive leverage. The authors argue that "the stronger is the ex-ante belief that securities are safe, the higher is the borrowing against them, and the more extreme the fire sales" (p. 466). They say that financial sector reform should go beyond just regulating the amount of leverage in the system and also include new financial innovation, particularly the creation of new claims (securities).

d) Debt and firm level productivity

LW (2014) is one of the few studies in the literature to document the relationship between the use of finance and productivity growth at the firm-level. They make use of firm level data available through Bureau van Dijk that constructs the data set from regulatory filings for firms in each European country. They focus on four large European countries – France, Italy, Spain and UK – and find that debt growth leads to future TFP growth for firms (a 10 per cent increase in debt leads to productivity increases between 0.8 and 2.1 per cent). They obtain similar results when they look at labor productivity instead of TFP and also when the definition of financing is either debt or equity financing.

In order to mitigate concerns regarding reverse causality prevalent in trying to disentangle the impact of debt on productivity, LW 2014 decompose TFP into an expected (inside the information set of the firm) and unexpected component (outside the information set of the firm) (as done by Levinsohn and Petrin, 2003).[30] They find that the relationship between debt growth and future productivity growth arises mainly due to the part of productivity that is outside the information set of the firm. Furthermore, the authors find that the relationship between debt growth and TFP growth strengthens with the increase in financing costs (proxied by spread on sovereign bonds for the 4 countries in the sample). The authors highlight the economic significance of the debt and productivity nexus by showing that the slowdown in debt growth in the aftermath of the Great Recession contributed to lower output growth. Their finding is in line with the

[29] Kalemli-Ozcan et al use AMADEUS for firm level data.

[30] The way this is done is by looking at the material inputs available for the firm which would have direct impact on the future productivity of the firm. This would be expected TFP – inside the information set of the firm.

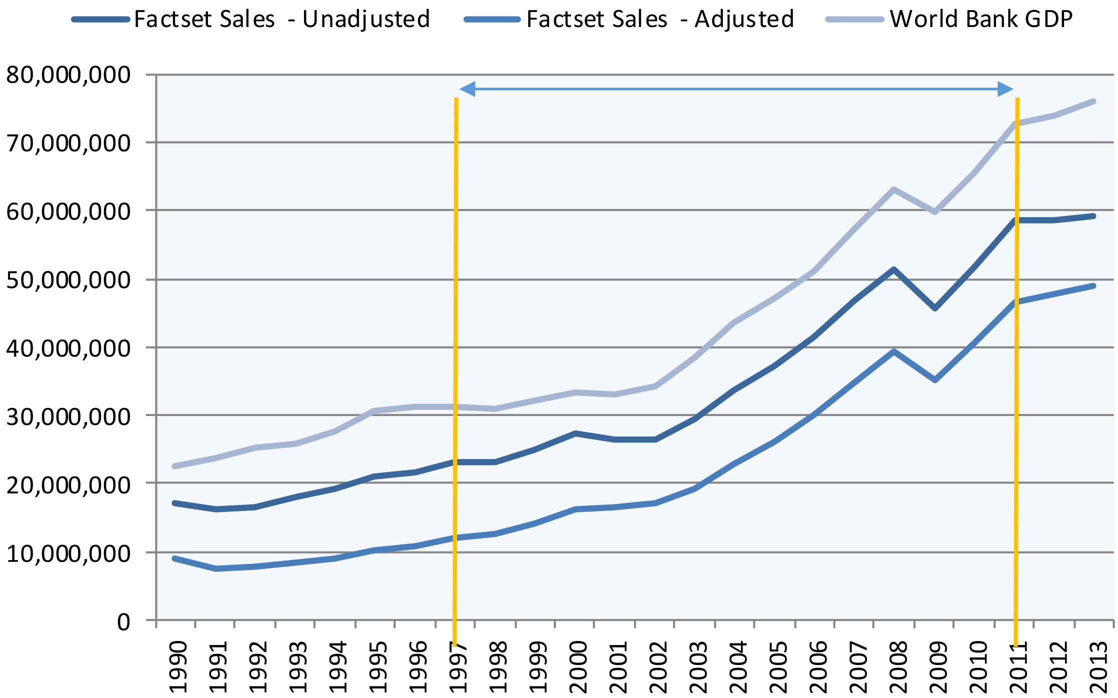
papers discussed earlier that show that financial crises lead to misallocation in capital and have a negative impact on output, which tends to persist.
There is a strand of literature that shows the link between financial development at the country level and the impact on firm level productivity. Most notable among these studies is the one by Beck, Levine and Loyaza (2000) who show that financial intermediaries affect economic development primarily by influencing total factor productivity (TFP). Their results hold using different indicators of financial development and also when accounting for potential endogeneity (employing an IV estimator and dynamic panel estimator).

2.4 Data and summary statistics

In a growing trend of private data providers used in academic research, FactSet is one that contains publicly listed firms in over 100 countries, covering the time period between the late 1970s and 2014. What makes the database particularly attractive for researchers looking into firm dynamics and labor market outcomes is the data coverage in terms of countries, sectors and period. Indeed, a large number academic studies use FactSet or similar databases. Compustat North America particularly is a popular choice in the finance and macro-finance literature – this database is a subset of FactSet, as coverage of the later has a global scope. Overall, much of the growth in the use of firm level data in the economic literature has relied on databases that retrieve the data from public financial statements; thus the use of FactSet can be considered standard in academic research. For instance, a search in Google Scholar with the key word Compustat returns approximately 37,000 results, 17,500 for 2010 or after. A search for FactSet returns 1,800 results, 1,300 of which for 2010 or after. Thus, Factset is not as popular as Compustat in academic research, but it is starting to become more popular.

One of the limitations of FactSet is that it contains only publicly listed firms, hence it is missing an important component of the production side of the economy – privately held companies. Aside from this, the dataset presents further limitations, such as asymmetry in collection between countries and regions, delays in data collection, illogical entries, etc. Despite all the limitations, after a careful cleaning up, we can build a sample that allows us to do sound empirical analysis. Figure 1 shows the GDP in current USD from the World Development indicators of the World Bank and total sales figures for all companies using FactSet. As it is expected, the levels from Factset substantially differ from the WDI GDP, which is natural given that aggregate sales do not correspond with GDP – aggregate sales are not obtained through a value added approach, and only a fraction of global production is captured by FactSet. Sales for adjusted data are substantially smaller than for unadjusted data – also to be expected as the adjustment removes firms from the database, hence from the total sales. The adjustment process is simply considering firms that present data for 2013 – this dampens the bias of availability of more recent data. Given the restrictions we choose 1997-2011 as the sample to work with, as can be seen in Figure 1, the level of consistency of the data for the selected period is acceptable.

Figure 1: World GDP from the WDI vs. aggregate sales from Factset



After cleaning up the database– where the key criterion was availability of employment information – the total sample we have is 71,672 firms, out of which 18,918 are in the United States. We select the 6 countries with the largest number of firms.

Table 1: Selected countries and number of firms

United States	18918
Japan	5200
United Kingdom	5049
Canada	5037
China	3611
India	3368

The following tables present summary statistics for the principal variables used in the regression analysis. Across countries it can be seen that the summary statistics do not differ drastically, the two developing countries, China and India, present higher median growth rates in TFP, Debt, and Sales, at the same time they present a narrower range in the level of capital expenditure and total assets.

Table 2: Median, 10th and 90th percentile of TFP growth rate

Country	10th percentile	50th percentile	90th percentile
Canada	-0.37	0.02	0.62
China	-0.39	0.09	0.53
United Kingdom	-0.22	0.06	0.36
India	-0.35	0.06	0.47
Japan	-0.33	-0.01	0.28
United States	-0.25	0.04	0.36
Total	-0.26	0.05	0.40

Table 3: Median, 10th and 90th percentile of debt growth rate

Country	10th percentile	50th percentile	90th percentile
Canada	-0.54	0.03	0.85
China	-0.26	0.14	0.68
United Kingdom	-0.57	0.03	0.87
India	-0.36	0.06	0.62
Japan	-0.37	-0.01	0.36
United States	-0.50	0.00	0.82
Total	-0.44	0.02	0.65

Table 4: Median, 10th and 90th percentile of sales growth rate

Country	10th percentile	50th percentile	90th percentile
Canada	-0.39	0.10	0.77
China	-0.16	0.16	0.51
United Kingdom	-0.27	0.09	0.55
India	-0.30	0.09	0.48
Japan	-0.15	0.05	0.23
United States	-0.26	0.08	0.57
Total	-0.22	0.08	0.48

Table 5: Median, 10th and 90th percentile of capital expenditure, million USD

Country	10th percentile	50th percentile	90th percentile
Canada	0.04	2.00	84.17
China	0.68	9.79	97.69
United Kingdom	0.13	3.30	102.53
India	0.06	2.45	48.65
Japan	0.38	7.93	159.85
United States	0.08	5.72	179.32
Total	0.12	5.27	134.16

Table 6: Median, 10th and 90th percentile of total assets, million USD

Country	10th percentile	50th percentile	90th percentile
Canada	0.51	21.41	826.18
China	38.44	203.33	1430.98
United Kingdom	5.73	72.35	1343.91
India	3.48	45.77	572.52
Japan	47.68	291.25	2883.82
United States	0.90	100.68	2776.88
Total	3.01	121.84	2047.88

2.5 Empirical Methodology

a) Estimating total factor productivity

One of the concerns regarding the study of the impact of debt on productivity is the possibility of reverse causality. When considering the relation between debt and productivity, expected productivity changes by the firm can affect decisions regarding debt. To alleviate these concerns of reverse causality we decompose TFP into expected and unexpected components – basically, one that is within the information set of the firm and one that is outside. Afterwards, the purpose of the analysis is to study the relationship between debt and the *unexpected* component of TFP. We follow the methodology used by Levinsohn and Petrin (2003) and some of the exercises considered in LW (2014). This approach does not guarantee that reverse causality does not drive the results, it does however, lessen the concern.

Here, Y_{it} is the output for i firm in year t, K_{it}, L_{it} and M_{it} are capital, labour and intermediate inputs. Output is proxied by sales, capital by plant and equipment, labor by the number of employees, and intermediate inputs by cost of goods sold minus labor expenses.[31] First of all, an estimate of value added is obtained by subtracting intermediate inputs from output:

$$VA_{it} = Y_{it} - M_{it}$$

Then we follow:

$$\log VA_{i,t} = c + \alpha\ logK_{i,t} + \beta\ logL_{i,t} + \omega_{i,t} + \eta_{i,t}$$

Where $\omega_{i,t}$ and $\eta_{i,t}$ denote the parts of TFP that are expected and unexpected to the firm in time *t*, this implies that: $\log TFP_{i,t} = \omega_{i,t} + \eta_{i,t}$. Presumably, the known component impacts the material input decision of the firm (intermediates) while the unknown component has no impact on that decision. In order to obtain the expected and unexpected components of TFP, we use Levinson and Petrin (2003) approach – TFP is regressed against a third degree polynomial of capital and intermediates inputs, thus the explanatory variables include: capital, capital square, capital cube, intermediates, intermediates square, intermediates cube, and the interaction between capital and intermediates terms.[32] In this model, the residual is the unexpected component of TFP. Additionally for the sake of establishing continuity with the LW (2014) results we consider in the first exercise the Cobb-Douglas TFP; in this case both components are used without any decomposition.

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[31] Cost of goods sold: the item represents all expenses *directly* allocated by the company to production, such as material, labor, and overhead.
Sales: This item represents gross sales (the amount of actual billings to customers for regular sales completed during the period) reduced by cash discounts, trade discounts, and returned sales and allowances for which credit is given to customers.
Property, Plant and Equipment: This item represents the cost of fixed property of a company used in the production of revenue before adjustments for accumulated depreciation, depletion, and amortization.
Number of employees: This item represents the number of company workers as reported to shareholders.
Labor expenses: This item represents the costs of employees' wages and benefits allocated to continuing operations.
Intermediates inputs are approximated as the total costs involved in production of the goods minus labor expenses. Total labor expenses are used due to data availability.

[32] Levine and Warusawitharana (2014) also follow the same approach.

b) Dynamic Panel Data Model

We use the following standard panel data model to examine the relationship between finance use and TFP at the firm level (Cameron and Trivedi, 2010; Wooldridge, 2010), in particular a dynamic panel data model:

$$\Delta TFP_{i,t+1} = \alpha_i + \delta \Delta TFP_{i,t} + \gamma \Delta d_{i,t} + x'_{i,t}\beta + \varepsilon_{i,t+1}$$

Where, $\Delta TFP_{i,t}$ refers to productivity growth in firm i, and year t, $\Delta d_{i,t}$ is debt growth, $x'_{i,t}$ are set of controls which include age of the firm, sales, capital expenditure, assets and year controls. Lastly, $\varepsilon_{i,t}$ is statistical noise. Another model is considered when trying to assess the effect of aggregate debt on firm level productivity.

$$\Delta TFP_{i,t+1} = \alpha_i + \delta \Delta TFP_{i,t} + \gamma \Delta d_{i,t} + \theta \Delta D_{j,t} + x'_{i,t}\beta + \varepsilon_{i,t+1}$$

The main change with respect to the previous equation is the additional term $\Delta D_{j,t}$, the growth of the country average of firm level logarithmic debt, i.e. for country j the magnitude is defined as:

$$Dj,t = \frac{\sum_{\forall i \in j} \ln(d_{i,t})}{\sum_{\forall i \in j} \mathrm{i}}$$

Additionally country level controls are added, in particular GDP and CPI[33] growth.

To estimate these equations one cannot use OLS or FE– see Bond (2002). We use the strategy suggested by Arellano and Bover (1995) and Arellano and Bond (1997) – they use lagged levels to estimate the first-difference equation and lagged differences to estimate the level equation. In this study, for the differenced equation, we use as instruments lag 2 of TFP growth[34] and the differences of all the controls and the variables of interest. To estimate the level equation, we use the difference of TFP at time t. The rest enter as predetermined variables. We set up this structure because the tests of autocorrelation point to order 1 autocorrelation and not order 2, and the Hansen tests of over identification do not reject the structure – both expected results if the specification is correct. Our methodology is very similar to Levine and Warusawitharana (2014).

2.6 Results

a) Firm level debt and firm level TFP

Table 7: (Cobb-Douglas) TFP and debt at the firm level, presents the results of the firm level data only model. The Cobb-Douglas TFP measure is used to benchmark our results with those of Levine and Warusawitharana (2014). The impact of debt growth at time t is positive on TFP growth at period t+1. Moreover the result is quite close to LW;

[33]Consumer Price Index.

[34] Using further lags as instruments does not change the results much - we use this specification because of its parsimony.

in fact, given that only one of the 6 countries in our sample coincides with the previous study and that our sample only includes publicly traded firms the finding is reassuring. We also see that TFP growth has a moderate tendency to mean reversion. The controls in contrast to LW, do not generally present any significant relation with TFP – except for capital expenditures - perhaps reflecting the smaller sample size.

Table 7: (Cobb-Douglas) TFP and debt at the firm level

Dependent variable: Growth TFP (t+1)	
	(1)
Growth TFP (t)	-0.12***
Log age (t)	-0.00
Growth sales (t)	0.03
Log capex (t)	-0.01*
Log assets (t)	0.01
Growth debt (t)	0.016***
No. of Obs.	16165
No. of Groups	3465
Year Dummy	Yes
Clustered SE	Yes
Firm Fixed Effects	Yes
Hansen test	0.66
AB test AR(2)	0.21

The dependent variable is the growth rate of the firm level estimated TFP at time t+1. As controls the growth rate of firm level TFP at time t, as well as the log of the age, the capital expenditures, and total assets, of the firm are included. The regression follows a Dynamic Panel Data model, and includes year and firm fixed effects. The last two lines report the p-value of the Hansen test of overidentifying restrictions and the AB AR(2) test of serial correlation. The variable of interest is the growth of firm level debt.

The baseline estimation of TFP for the present study is, as described above, based on the LP method not the direct Cobb-Douglas estimation. Table 8: (LP method) TFP and debt at the firm level presents the results. Both the tendency to mean reversion of TFP growth and the controls do not appear to change much. However this is not the case for the result of positive association between firm level debt and TFP growth, for our sample – and in contrast with Levine and Warusawitharana (2014) – the relation appears to derive from the expected component of TFP growth. A note of caution is required when comparing the results of the present study to those of LW, the sample that we use is smaller and only includes publicly listed firms, moreover the coefficients are of similar magnitude, and therefore we would not be surprised if improving the coverage of our sample resulted in the significance of the result.

Table 8: (LP method) TFP and debt at the firm level

Dependent variable: Growth TFP (t+1)	
	(1)
Growth TFP (t)	-0.15***
Log age (t)	0.00
Growth sales (t)	0.03
Log capex (t)	-0.01***
Log assets (t)	0.01
Growth debt (t)	0.005
No. of Obs.	16110
No. of Groups	3457
Year Dummy	Yes
Clustered SE	Yes
Firm Fixed Effects	Yes
Hansen test	0.66
AB test AR(2)	0.21

The dependent variable is the growth rate of the firm level estimated TFP at time t+1. As controls the growth rate of firm level TFP at time t, as well as the log of the age, the capital expenditures, and total assets, of the firm are included. The regression follows a Dynamic Panel Data model, and includes year and firm fixed effects. The last two lines report the p-value of the Hansen test of overidentifying restrictions and the AB AR(2) test of serial correlation. The variable of interest is the growth of firm level debt.

b) Aggregate level debt and firm level TFP

In line with our proposal from the introduction– that the effects of aggregate and firm level debt should be analyzed separately - we now consider the effect of aggregate debt of firm level productivity. For several theoretical models proposed in the literature the effects of aggregate or firm level debt on firm productivity can easily differ – as is discussed in sections 1 and 2 above. Furthermore, the “contradictory” evidence found in the literature (the positive or negative effect on productivity) is often obtained from different data sets but the aggregate vs firm level distinction is not considered. This, the theoretical and empirical discrepancies, in our view are sufficient reason to study specifically if and how both effects differ.

When considering aggregate debt by country and year, its relationship with firm level productivity appears to be clearly negative– in contrast to firm level debt - (Table 9: Aggregate debt and TFP). Moreover, the coefficient is different than zero at any of the usual significance levels. The table below presents three different regression exercises. The first considers the impact of aggregate debt growth on the whole available sample, the second restricts the sample to firms with available data on firm level debt, and finally the third considers the firm level and aggregate debt growth at the same time.

The effects appear to coexist, without any substantial change in any of the size of each effect.

Table 9: Aggregate debt and TFP

Dependent variable: Growth TFP (t+1)			
	(1)	(2)	(3)
Growth TFP (t)	-0.14***	-0.14***	-0.15***
Log age (t)	0.00	0.00	0.00
Growth sales (t)	0.03**	0.01	0.02
Log capex (t)	-0.01***	-0.01***	-0.01***
Log assets (t)	0.00	0.01*	0.00
Growth debt (t)			0.005
Growth average debt (t)	-0.09***	-0.12***	-0.11***
No. of Obs.	23203	16110	16110
No. of Groups	4337	3457	3457
Year Dummy	Yes	Yes	Yes
Clustered SE	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes
Hansen test	0.75	0.45	0.68
AB test AR(2)	0.78	0.98	0.65

The dependent variable is the growth rate of the firm level estimated TFP at time t+1. As controls the growth rate of firm level TFP at time t, as well as the log of the age, the capital expenditures, and total assets, of the firm are included. The regression follows a Dynamic Panel Data model, and includes year and firm fixed effects. The last two lines report the p-value of the Hansen test of overidentifying restrictions and the AB AR(2) test of serial correlation. The variables of interest are the growth of firm level debt and of country level firm debt.

c) Impact of aggregate debt controlling for aggregate characteristics

In light of the negative association between aggregate debt and the firm level TFP, we considered controlling for GDP and CPI growth. Table 10: Controlling for GDP and CPI, presents four regressions: the first and second control for GDP contemporaneously and in the next period respectively. The third controls for CPI growth in period t, and the last controls for both GDP and average CPI growth in period t+1. The results do not show much impact on the estimated coefficient of growth in average debt which remains at -0.11 with a 2 digit precision. It is worth highlighting the implications of the last result. Country level average debt growth in time t is found to have a negative impact on firm level TFP growth in time t+1, even after controlling for GDP and CPI growth in t+1, therefore the observed results are not likely to be a consequence of a shock that affects GDP or prices (measured by CPI) at the aggregate level, directly or indirectly, and this, in turn, has an impact on aggregate debt.

Table 10: Controlling for GDP and CPI

Dependent variable: Growth TFP (t+1)				
	(1)	(2)	(3)	(4)
Growth GDP (t)	-0.07		-0.05	
Growth GDP (t+1)		0.12		0.18
Growth CPI (t)			-0.00	
Growth CPI (t+1)				-0.00
Growth debt (t)	0.005	0.005	0.005	0.005
Growth average debt (t)	-0.11***	-0.11***	-0.11***	-0.11***
No. of Obs.	16110	16110	16110	16110
No. of Groups	3457	3457	3457	3457
Clustered SE	Yes	Yes	Yes	Yes
Usual controls	Yes	Yes	Yes	Yes
Year controls	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes
Hansen test	0.69	0.67	0.67	0.67
AB test AR(2)	0.65	0.65	0.66	0.66

The dependent variable is the growth rate of the firm level estimated TFP at time t+1. As controls the growth rate of firm level TFP at time t, as well as the log of the age, the capital expenditures, and total assets, of the firm are included. The regression follows a Dynamic Panel Data model, and includes year and firm fixed effects. The last two lines report the p-value of the Hansen test of overidentifying restrictions and the AB AR(2) test of serial correlation. The variables of interest are the growth of firm level debt and of country level firm debt. Additionally the effect of aggregate controls, GDP and CPI, at time t and t+1 are considered.

d) Suggestive evidence of the mechanism

We present a final exercise that suggests the possible cause of the negative influence of country debt growth on firm level TFP growth. Two different mechanisms can be considered a priori, one relies on economy wide debt as the driver of the negative relation between debt and TFP, the other on sectoral debt. Identifying an economy wide vs a sectoral mechanism provides a step towards understanding the effect. The results are shown in Table 11: Sectoral and Country level debt. The conclusion is clear, whereas sectoral debt has a negative impact on firm level productivity by itself, when both the sectoral and country level debt are considered, the former loses its significance. Therefore the mechanism appears to work on an economy wide basis. This is relevant in proposing a mechanism to account for the empirical evidence, in particular mechanisms based on channels that are likely stronger at the sector level than in aggregate (such as those based on the labor market) should at least be considered as less plausible than potential alternatives.

Table 11: Sectoral and Country level debt

Dependent variable: Growth TFP (t+1)		
	(1)	(2)
Growth TFP (t)	-0.15***	-0.15***
Log age (t)	0.00	0.00
Growth sales (t)	0.02	0.02
Log capex (t)	-0.01***	-0.01***
Log assets (t)	0.01*	0.01**
Growth debt (t)	0.005	0.005
Growth average debt (t)		-0.11***
Growth average sector debt (t)	-0.04**	0.00
No. of Obs.	16110	16110
No. of Groups	3457	3457
Usual controls	Yes	Yes
Year Dummy	Yes	Yes
Clustered SE	Yes	Yes
Firm Fixed Effects	Yes	Yes
Hansen test	0.68	0.68
AB test AR(2)	0.62	0.65

The dependent variable is the growth rate of the firm level estimated TFP at time t+1. As controls the growth rate of firm level TFP at time t, as well as the log of the age, the capital expenditures, and total assets, of the firm are included. The regression follows a Dynamic Panel Data model, and includes year and firm fixed effects. The last two lines report the p-value of the Hansen test of overidentifying restrictions and the AB AR(2) test of serial correlation. The variables of interest are the growth of country-sector level and of country level firm debt.

Based on the results of this exercise – suggesting an economy wide mechanism – together with the results of the section above – mitigating the concerns of reverse causality – we present the following hypothesis. The hypothesis has two parts, the first is that debt and real estate prices at the aggregate level have a positive link, in either or both directions. The second is that aggregate real estate prices (both sale price and rental) have ceteris paribus a negative impact on firm level productivity. The reason is almost an accounting identity, higher real estate prices in aggregate for a firm that remains with the same factor input and sales can have a negative effect on productivity by lowering value added (due to increased rental costs and thus lower operating income). Alternatively, a firm that acquires a new property at a higher nominal valuation than the firm's own existing real estate does not see an increase in value added proportional to the increase in the nominal real estate stock.

Furthermore regarding the potential divergence of the effect of aggregate real estate valuation or firm real estate valuation (and thus also possibly debt) is a clear possibility since the increase of an individual firm valuation will (1) not increase rental expenses (2) actually increase the capital of the firm (and not necessarily at a lower rate than the nominal increase).

To test whether our hypothesis justifies the results we present two exercises. In the first case we run the same regression as in the previous exercises, however in this case we use a much cruder proxy of productivity, unadjusted labor productivity. The unadjusted measure is defined as:

$$\log Unadjusted\_Labour\ Productivity_{i,t} = \log Sales_{i,t} - \log Employees_{i,t}$$

This measure, despite its obvious drawbacks, has the advantage of not being affected – in an accounting sense – from changes in real estate prices, simply: rental cost do not enter the output proxy (Sales) and higher valuations of real estate do not enter the input proxy (Employees). Table 12: Effect on unadjusted proxy of labor productivity reports the results. The regression model used is the same as in the exercises above, as it can be seen the results are clear. Average debt is no longer significant at any usual significance level, unsurprisingly GDP growth has now a clear effect, since the proxy of productivity growth has sales growth - a clearly procyclical variable- entering directly in its definition[35].

Table 12: Effect on unadjusted proxy of labor productivity

Dependent variable: Growth Labor Productivity (t+1)		
	(1)	(2)
Growth GDP (t)	1.08***	0.92***
Growth average debt (t)	0.01	0.01
No. of Obs.	90437	98661
No. of Groups	15032	16417
Usual controls	Yes	Yes
Year Dummy	Yes	Yes
Clustered SE	Yes	Yes
Firm Fixed Effects	Yes	Yes
Lags Dependent Variable	2	1
Hansen test	0.049	0.015
AB test AR(2)	0.309	0.01

The dependent variable is the growth rate of the firm level estimated TFP at time t+1. As controls the growth rate of firm level TFP at time t, as well as the log of the age, the capital expenditures, and total assets, of the firm are included. The regression follows a Dynamic Panel Data model, and includes year and firm fixed effects. The last two lines report the p-value of the Hansen test of overidentifying restrictions and the AB AR(2) test of serial correlation. The variable of interest is the growth of country level firm debt. Regression (1) considers 2 lags of the dependent variable, whereas (2) considers only one.

Another exercise is carried out to test the hypothesis that the negative relation between average debt and firm level productivity growth. In particular we develop a proxy for country level real estate nominal value. At the firm level the proxy is simply: Property plant and equipment – Equipment (following the definition in the previous section). This will simply reflect the cost of real estate assets for the firm, or $\boldsymbol{re}$. Then as in the derivation of average debt, we obtain the country average of the log variable.

[35] The Hansen test rejects the over identifying restrictions at the 5 and 10 % confidence level, but not at the 1%. Several other specifications are tried in order to achieve acceptable results both in the Hansen test and the AB test, nonetheless no clearly preferable results are obtained, and to avoid falling in a trap of data mining we maintain the same regression structure than for the rest of the exercises. For illustrative purposes we consider 2 different specifications.

$$RE_{j,t} = \frac{\sum_{\forall i \in j} \ln(re_{i,t})}{\sum_{\forall i \in j} \text{i}}$$

Afterwards, using the same regression model we test the effects of adding the real estate proxy. We present 2 specifications following the same model as in column 1 Table 9. The results are reported in Table 13: Controlling for Country level Real Estate Value. Other specifications, deliver qualitatively similar results. The overall conclusion that can be reached is that, when including the average real estate valuation and not the average debt, the former presents a negative and significant impact on TFP. The second is that when introducing both variables, average debt loses its significance whereas the real estate proxy in some cases does whilst it does not in others.

Table 13: Controlling for Country level Real Estate Value

Dependent variable: Growth TFP (t+1)			
	(1)	(2)	(3)
Growth TFP (t)	-0.14*	-0.15*	-0.14
Growth CPI (t)			0.00
Growth real estate average nominal value (t)	-0.07*	-0.08***	-0.08***
Growth average debt (t)	-0.02		
No. of Obs.	23203	23203	23203
No. of Groups	4337	4337	4337
Usual controls	Yes	Yes	Yes
Year Dummy	Yes	Yes	Yes
Clustered SE	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes
Hansen test	0.76	0.76	0.59
AB test AR(2)	0.79	0.79	0.84

The dependent variable is the growth rate of the firm level estimated TFP at time t+1. As controls the growth rate of firm level TFP at time t, as well as the log of the age, the capital expenditures, and total assets, of the firm are included. The regression follows a Dynamic Panel Data model, and includes year and firm fixed effects. The last two lines report the p-value of the Hansen test of overidentifying restrictions and the AB AR(2) test of serial correlation. The variables of interest are the growth of country level firm debt and real estate proxy value. Additionally the effect of the aggregate controls, GDP and CPI, at time t is considered.

A final exercise exploring the hypothesis is carried out. If real estate prices are the cause of the negative association between country level debt and firm level productivity, and furthermore if the uncovered previous relation between the proxy of country level real estate value and firm TFP is due to its relation to debt, then there is cross sectional variation to be exploited. Particularly if the postulated hypothesis is indeed a causal mechanism we would not expect it to have the same strength for all country-sector pairs in the sample. For firms operating in country-sector pairings which require a high degree of real estate to operate we would expect a high impact, of debt and of real estate prices, on firm level productivity. Conversely, for firms operating in country-sector pairings with a low utilization of real estate, we would expect a much lower impact[36]. We put to test this hypothesis in the following exercise. The “real estate intensity” of a country sector pair is simply measured by the (aggregate) ratio of the real estate proxy to total assets, for all firms operating in that country and sector. Following the notation used above, the intensity of real estate usage of a country-sector pair, *j*, is:

$$Ratio_j = \frac{\sum_{\forall i \in j} re_i}{\sum_{\forall i \in j} TotalAssets_i}$$

The country-sector values above the average ratio are considered of high real estate intensity, whereas those with values below average are considered to be of low real estate intensity. The results are presented in Table 14: Splitting the sample across high and low real estate to assets ratio country-sector pairs. The same specification from the rest of the study is used[37]. The results are clear: in country-sectors with high intensity of real estate both aggregate firm debt and the proxy of real estate value have a clear negative effect on firm level productivity. On the other hand, in country-sectors where the intensity is low, neither variable has a significant impact on firm level TFP.

[36] The reason is a straightforward matter of magnitude, for instance: the impact on value added of a 10% increase in rental expenses is higher if the rent represents 50% of operating income than 1%.

[37] As it can be seen for some specifications the Hansen test presents p values above 0.01 but below 0.05, yet the same specification is maintained; given the large potential pool of models this is done to avoid opening the door to data mining. Additionally the AB test indicates that at least a DPD model is still justified.

Table 14: Splitting the sample across high and low real estate to assets ratio country-sector pairs

Dependent variable: Growth TFP (t+1)				
Real estate intensity of the country- sector where the firm operates:	High	Low	High	Low
	(1)	(2)	(3)	(4)
Growth GDP (t)	-0.26**	-0.14	-0.26**	-0.14
Growth real estate average nominal value (t)	-0.10***	-0.00		
Growth average debt (t)			-0.14***	0.02
No. of Obs.	9577	13626	9577	13626
No. of Groups	1805	2532	1805	2532
Clustered SE	Yes	Yes	Yes	Yes
Usual controls	Yes	Yes	Yes	Yes
Year controls	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes
Hansen test	0.03	0.10	0.04	0.10
AB test AR(2)	0.10	0.41	0.10	0.40

The dependent variable is the growth rate of the firm level estimated TFP at time t+1. As controls the growth rate of firm level TFP at time t, as well as the log of the age, the capital expenditures, and total assets, of the firm are included. The regression follows a Dynamic Panel Data model, and includes year and firm fixed effects. The last two lines report the p-value of the Hansen test of overidentifying restrictions and the AB AR(2) test of serial correlation. The variables of interest are the growth of country level firm real estate proxy value and debt. Additionally the effect of an aggregate control, GDP at time t, is considered. The exercise is performed in two sub-samples, sector-country pairs with an above average real estate proxy to total assets are considered for (1) and (3), and for (2) and (4) the rest of the sample is used.

The results of all three exercises thus support the hypothesis that there is a link between country level debt and country level real estate valuations, and that the latter has a negative impact on firm level TFP.

2.7 Conclusion

By employing firm-level data covering 71,672 firms from Canada, China, India, Japan, the United Kingdom and the United States, this chapter shows that firm level debt is positively associated with future TFP of the firms in question, but that aggregate debt has a statistically significant negative impact on future TFP. The latter result is notable as it seems to corroborate the finding from the macro-econometric literature that shows that aggregate debt could have a negative impact on economic growth, particularly beyond a certain threshold (see Cecchetti and Kharroubi, 2012; Arcand, Berkes and Panizza, 2011).

Our study puts forward a hypothesis to explain the negative relationship between aggregate debt and firm level productivity. This is that debt and real estate prices are positively linked at the aggregate level, while aggregate real estate prices have a negative impact on firm level productivity. The reason is almost an accounting identity. Higher real estate prices in aggregate for a firm that remains with the same factor input and sales can have a negative effect on productivity by lowering value added (due to increased rental costs and thus lower operating income). Alternatively, a firm that acquires a new property at a higher nominal valuation than the firm's own existing real estate does not see an increase in value added proportional to the increase in the nominal real estate stock.

Indeed, results from our empirical exercise lend support to this hypothesis. There is a link between country level debt and real estate valuations, and both tend to have a negative impact on firm TFP. Furthermore, a productivity measure robust to real estate valuations does not present the negative impact of aggregate debt on firm level productivity. Finally, we split the sample according to the "real estate intensity" of the country sector pairs present. We find that the impact of aggregate debt on firm level TFP is significant and negative for those firms operating in high real estate intensity environments, but that it is not significant in low real estate intensity ones.

3. Productivity movements during turning points of recessions

3.1 Abstract

Using the recently released database of quarterly utilization adjusted productivity (based on Basu, Fernald, and Kimball 2006, or BFK) I uncover 3 new facts concerning productivity and recessions. During turning points, the 1st quarter of recession and the 1st quarter of recovery, (1) adjusted productivity growth is significantly lower and higher than for the rest of the sample, (2) the output - adjusted productivity correlation is significantly higher than for the whole sample, and (3) for the overall sample excluding turning points the output - adjusted productivity correlation is substantially lower than for the overall sample and significantly lower than during turning points.

These facts are not found in other quarters near turning points, and are very uncommon in random sets of quarters. Furthermore related variables such as GDP, employment or TFP do not present such behavior. Several robustness checks corroborate that the stylized facts do not have a mechanical or naive cause.

Using simulations and econometric analysis I show that the stylized facts cannot plausibly be considered technology shocks, in the sense of exogenous technology movements. Rather they seem to be caused by another driving force. Some exercises point to demand as a reasonable candidate for such a role.

The hypothesis that technology shocks are the cause of the stylized facts has a sizeable impact on the debate regarding the role of technology as a driver of the business cycle. If correct, it raises the possibility that such shocks are behind the start and end of recessions. If this hypothesis is invalid - as this study argues- the role of technology in the business cycle is reduced, and it limits the methods to obtain technology shocks using the BFK database.

3.2 Introduction

The role of technology shocks as drivers of aggregate fluctuations is a central debate in macroeconomics. The results are far from homogeneous and can be categorized into three broad groups. Empirical studies based on long run restrictions assign only a minor role to technology as a driver of the business cycle. This result was first stated in the seminal paper of Galí (1999), and was subsequently confirmed, for instance in Francis and Ramey (2005). Another broad category corresponds to results of medium scale DSGE models. For instance in Smets and Wouters (2007) technology shocks can play a sizable role even in the short run, accounting for 8 to 20% of the variance of output for horizons of one year or less. Finally, at the other end of the spectrum there is the old and new RBC literature. As it is well known, early RBC literature claimed technology as the primary driver of the business cycle. In a more recent contribution McGrattan and Prescott (2012) are able to replicate the great recession on the basis of productivity shocks. In general, papers using SVAR (Structural Vector Autoregression) models tend to allocate only a small role to technology in the business cycle. A Structural Vector Autoregression model is a multivariate, linear representation of a vector of variables on its own lags and possibly other variables, trends and constants. Contrary to Vector Autoregressions, SVAR models contain an explicit identifying assumption that allows them to recover meaningful economic shocks from the observables[38].

The production of a new database has awakened interest in this last element, the results using SVAR models. The database in question is a quarterly utilization adjusted productivity database - introduced in Fernald (2012), which is based on the methodology of Basu, Fernald, and Kimball (2006). Having access to such a database is crucial if one wants to identify technology shocks with only transitory effects on productivity. Otherwise the obtained shocks could be nothing more than a variation in factor utilization: labor effort and workweek of capital (the utilization rate of capital). As commented on in Fernald (2012), a measure of unadjusted TFP can hardly provide a quarterly measure of technology change, as utilization intensity varies strongly at a quarterly frequency. The reason is that variable utilization is often modeled, for instance see Solow (1964) or Galí and van Rens (2010), as a margin of adjustment more flexible than factor input. As a consequence, utilization presents high variability in the short run and thus unadjusted TFP provides a poor measure of technological change.

The reopened debate regarding the role of technology shocks using SVAR models is due to Sims (2011). Using the novel quarterly utilization adjusted productivity database and a SVAR model the author finds that technology shocks can explain up to 60% of the cyclical variations in output. The main reason for the difference in results arises from the identification of technology shocks. In contrast to previous articles, the author identifies technology shocks not only as shocks with permanent effects on productivity, but also allows shocks to have just transitory effects. The introduction of this new methodology is justified by the availability of utilization adjusted productivity, as mentioned above.

Therefore the role of technology shocks in aggregate fluctuations identified by SVAR models remains an open question, particularly when this new dataset - the Fernald (2012) database - is being used. This chapter contributes to this debate by analyzing the relationship between the empirical behavior of adjusted productivity and the business cycle. In particular, I uncover 3 previously unknown facts about the behavior of adjusted productivity. These facts concern turning point quarters, the beginning and the end of recessions. Thus, turning points are defined as the 1st quarter of a recession and the 1st quarter of a recovery. The 1st fact is that during turning points, adjusted productivity growth is significantly different than during the overall sample. In particular, during the 1st quarter of a recession, adjusted productivity decreases producing a significantly lower than average growth rate. On the other hand, during the 1st quarter of a recovery, the adjusted productivity growth rate is significantly higher than on average. In short, adjusted productivity procyclical spikes are observed during turning points. Crucially, other quarters of recession or recovery do not present this phenomenon. The 2nd fact is that during such turning points, the correlation between output and adjusted productivity is significantly and substantially higher than the correlation for the whole sample. Finally, the 3rd fact is that if one excludes turning points, and thus focuses on the rest of the sample, the correlation between output and adjusted productivity is substantially lower than in the overall sample, and, furthermore, significantly and substantially lower than the correlation during turning points[39]. All these facts are corroborated using a statistical test, the first using a t-test of mean comparison, and the last two using confidence bounds for correlations, with the results being significant at usual levels. To complement the uncovering of these stylized facts, I

[38]See the notes by Fernández-Villaverde and Rubio-Ramírez, on the former's teaching page, for a short and clear exposition. At the time of writing the link is:
http://economics.sas.upenn.edu/~jesusfv/svars_format.pdf.

[39]I comment below why 2 does not necessarily imply 3.

perform several robustness checks to ensure their relevance, discarding causes such as: random chance, extreme output movements during turning points, inter- and intra-sectoral reallocation, and the behavior of closely related variables. Importantly, this last exercise takes into account GDP growth, which does not exhibit the same behavior as adjusted productivity. Whilst it is true that during the first quarter of recession GDP growth is significantly lower than average, and during the first quarter of recovery is significantly higher, the same is true both for the next quarter of recession and for the next 3 quarters of recovery, whereas for adjusted productivity it is not.

The above discussion shows that turning points are important for understanding the ability of the shocks that can affect adjusted productivity in driving the business cycle. The reason is twofold. First, given that the adjusted productivity spikes coincide precisely with the start and end of recessions, it is natural to enquire about a potential causal link[40]. Second, the result of stylized facts 2 and 3 is that the bulk of the correlation between adjusted productivity and output is due to turning points. Thus, if one wants to assess quantitatively[41] the impact of adjusted productivity on output and the business cycle, the analysis must take into account turning points. Both reasons show the importance of better understanding the behavior of adjusted productivity during turning points.

The second contribution of the study is concerned with investigating the source of the uncovered facts described above. First, I consider whether exogenous movements in technology - technology shocks - are a plausible candidate as a cause of the stylized facts. To answer this question, I perform a simulation exercise. In particular, I carry out simulations of a standard RBC model and a medium scale NK model, feeding them a simulated technology shock compatible with adjusted productivity behavior. The resulting pattern does not match the empirical counterpart. The exercise suggests that the hypothesized technology shocks are not capable of generating the observed behavior in output and technology. As an alternative, I consider whether the observed movements of output and productivity during turning points could be caused by demand factors. To assess the likelihood of demand being the cause of the stylized facts, I consider two different pieces of evidence. First, I estimate demand shocks using a SVAR model and analyze their correlation with adjusted productivity at the quarterly frequency. Such a correlation is essential to explain the turning point stylised facts: the residuals of an OLS regression between adjusted productivity and the estimated demand shocks do not present the behavior described as stylized facts. Furthermore, the Impulse Response Function of adjusted productivity to a demand shock shows a significant response for just one quarter and a flat response afterward. This last result is fully consistent with demand shocks causing turning points and the adjusted productivity behavior during these periods[42]. Crucially steps are taken to ensure that the estimated demand shocks cannot be plausibly interpreted as technology shocks. Second, I consider two plausible demand indicators, and examine whether they present a similar behavior as adjusted productivity during turning points. Overall the results of the exercises point to demand being a plausible cause of the stylized facts. However, further research is necessary before such a conclusion can be drawn.

The importance of whether or not the stylized facts are caused by technology shocks is substantial. If, bearing in mind the size of the productivity movements and their timing, which is precisely during turning points, they are interpreted as technology shocks, then the movements could be the cause of both recessions and subsequent recoveries and

[40]A priori in either direction.

[41]Or even qualitatively given the magnitude of the phenomena.

[42]The fact that the results show consistency with this scenario does not prove that this is in fact the case.

thus much of the business cycle variation of output. On the other hand, if the movements of productivity are not caused by technology shocks - and this is the main conclusion of the present study - their role in business cycle fluctuations is considerably diminished. Because the correlation between output growth and adjusted productivity growth is substantially smaller if turning points are removed from the sample, their influence on output at business cycle frequencies will necessarily decrease.

3.3 Data

Several databases are used in this study. The main one is the quarterly database of utilization adjusted productivity described in Fernald (2012), based on the adjustments of Basu, Fernald, and Kimball (2006). The data at the moment of retrieval spanned the period between 1947:Q2 to 2014:Q3. The main variables are the growth rate of output, hours worked and several productivity measures: total factor productivity (TFP), total factor productivity for the investment sector, and total factor productivity for the consumption sector (CTFP). Each of these measures is also available adjusted for factor utilization, I refer to adjusted total factor productivity as ATFP, and adjusted consumption sector total factor productivity as ACTFP throughout this study. For a detailed description of the adjustment procedure see Fernald (2012); here I briefly summarize the procedure following Sims (2011). Output is obtained from capital and labour:

$$y_t = a_t (s_t k_t)^{\alpha} (e_t n_t)^{1-\alpha}$$

where a_t denotes technology, k_t capital, n_t labour (hours worked times number of workers), and crucially; s_t represents the workweek of capital (utilization of capital in the BFK terminology), and e_t workers' effort. These last two represent the variable utilization margin, and they are assumed to be unobserved by the econometrician and more easily adjustable by the firm. The *naive* Solow residual in continuous growth rates is estimated as:

$$\Delta \ln TFP_t = \Delta \ln y_t - \alpha \Delta \ln k_t - (1-\alpha) \Delta \ln n_t$$

which instead of measuring solely technological change, includes variations in the utilization margin. To filter this measure, BFK (2006) show that under certain conditions variation in hours worked can proxy variation in effort and workweek of the capital. The intuition is that a cost minimizing firm will modify inputs along all the available margins. Therefore a measure of utilization variation can be estimated, $\Delta \ln U_t = \alpha \Delta \ln s_t + (1-\alpha) \Delta \ln e_t$, which is in turn used to correct the raw Solow residual:

$$\Delta \ln ATFP_t = \Delta \ln TFP_t - \Delta \ln U_t$$

obtaining the growth rate of ATFP or adjusted total factor productivity. A similar procedure can be applied to CTFP, consumption (sector) total factor productivity, to obtain ACTFP, adjusted consumption total factor productivity. For the rest of the chapter I refer to any of the adjusted measures (ATFP and ACTFP or both) as Adjusted Productivity (AP).

A second database used is the FRED database. In particular it is used for data on GDP, employment, and most importantly quarterly NBER recession dating. This last measure is used to identify the turning points of a recession. To study possible relocation effects a sectoral and a firm level database are used. The former uses the NBER CES Manufacturing Industry Database, while the latter is based on Compustat Industrial Annual files.

3.4 The evidence

a) Stylized facts

Analyzing the quarterly growth of utilization adjusted productivity (both ATFP and ACTFP) during turning points reveals 3 previously unnoticed empirical regularities. Adjusted productivity growth presents the following characteristics:

1) An above (below) average growth rate of AP in the 1st quarter of recovery (recession), which is significantly different when a t-test is used.
2) A higher correlation of AP with output (in growth rates) during turning points than for the overall sample, which is significantly different when the confidence interval for the correlation is obtained.
3) A lower correlation of AP with output (in growth rates) during the rest of the sample (discarding turning points) than for the overall sample. Furthermore, the correlation is significantly lower than during turning points when the confidence interval for the correlation is used.

Before proceeding to describe each stylized fact I address the relationship between items 2 and 3. Although a higher than average correlation for a given subsample might seem intuitively to point to a lower than average correlation for the complementary subsample, this is not necessarily the case. Indeed the opposite can be easily observed[43]. For this reason, I consider them separate facts.

Figure 1 a and b plot ATFP and ACTFP average growth rates for the last 11 post war US recessions around turning points. The period considered spans 3 quarters before a recession starts, 1 quarter after, and 3 quarters after the recovery starts and two quarters before[44]. ATFP growth is substantially lower than average during Q1 of recession, and higher than average during Q1 of recovery. In the case of Q1 of recession, the sample average is not above the 90% upper bound; however, if tested, Q1 of recession presents

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[43]For instance, by simulating two subsamples that resemble the structure of having turning points (which tend to be more extreme in at least the realization of one variable) and normal periods the result that both turning points and normal periods have higher correlations than the overall sample can easily be obtained. Consider the following process: during normal periods $y_t = 2.5x_t + \varepsilon_t$, $x_t \sim N(0,5)$, $\varepsilon_t \sim N(0,5)$, during turning points the relation is $y_t = 0.9x_t + \varepsilon_t$, with the same distribution for ε_t. However for x_t, instead of a single d.g.p. two different ones are considered. The one to mimic Q1 of recessions (occurrences with lower average realizations) follows $x_t \sim N(-2, 0.5)$, whereas the one to mimic Q1 of recoveries (occurrences with higher average realizations) follows $x_t \sim N(2, 0.5)$. Simulating a sample of 1000 normal periods and 100 turning points (roughly the proportions empirically observed), the following correlations are obtained: for the overall sample 82.7%, for the normal period subsample 91.9%, and for the turning points subsample 97.2%.

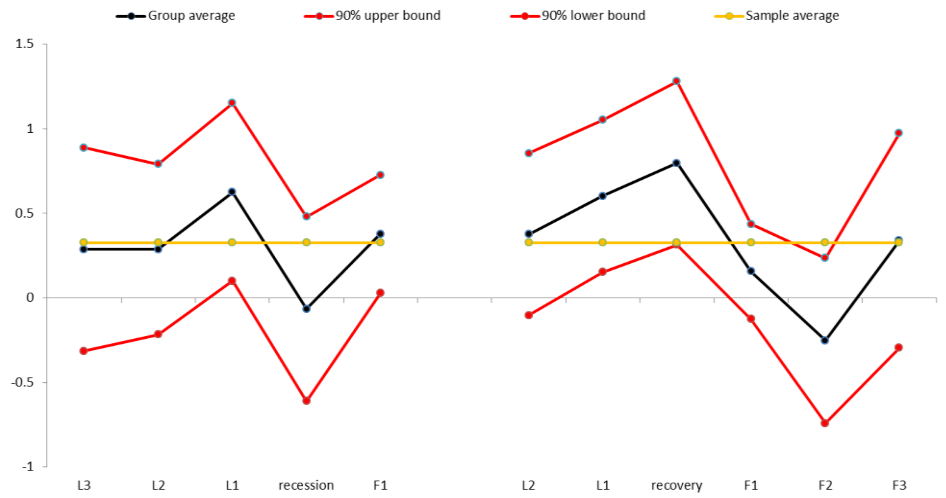
[44]Including Q3 of a recession would mix recession quarters with Q1 of a recovery, as there is a recession in the sample that only lasts for two quarters.

lower ATFP than the rest of the sample at a 10% significance level. The disparity is caused by the fact that removing Q1 of recession from the sample average pushes the magnitude upwards. In the case of ACTFP[45] the results are clearer, with Q1 of recession presenting a lower growth rate than the lower bound. Table A1 in the appendix formally tests the hypothesis of abnormal growth rate during each quarter with one sided t-tests and confirms the results. Growth rates of both ATFP and ACTFP during Q1 of recession and recovery are below and above the rest of the sample growth rate at the usual significant levels. In contrast, Q2 of both recession and recovery are not characterized by an unusual growth rate of either productivity measure. In fact, for the whole horizon, aside from turning points, only Q3 of recovery presents an unusual growth rate. Q3 of recovery presents a low growth rate of both ATFP and ACTFP. I do not consider this to be part of the stylized facts. The reason is twofold. First, the stylized facts 2 and 3 regarding correlation do not hold for this quarter. In both cases, for ATFP and ACTFP, during Q3 of recovery, the correlation with output is not only clearly smaller than during turning points, but smaller than the correlation for the rest of the sample (excluding turning points and Q3 of recovery). And second, the unadjusted measure of TFP does not exhibit such behavior. Figure 2 shows TFP around turning points, as in the case of Figure 1. Aside from the previous point, by using the unadjusted measure of productivity it can be observed that turning points present the largest (positive and negative) growth rates compared to other quarters. It can be concluded that the abnormal growth rates of adjusted productivity are not only a consequence of the filtering procedure. Indeed, the growth rate is already below and above average in the raw TFP data.

[45]I consider this measure for two reasons. First, TFP behaves differently during recessions in the investment and consumption sectors. Second, the consumption sector represents around 75% of overall GDP during the sample period, which makes it a natural magnitude to focus on when analyzing productivity.

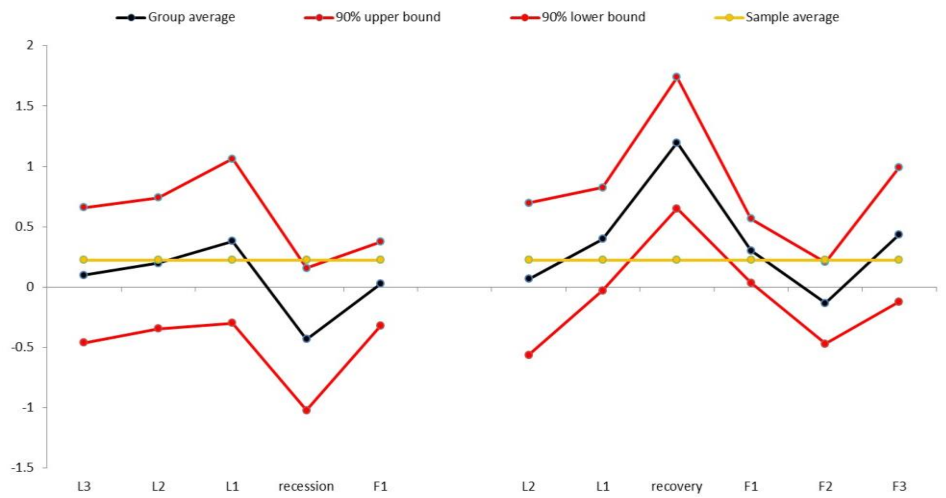
Figure 1 - Productivity growth around recessions

Figure 1a - ATFP



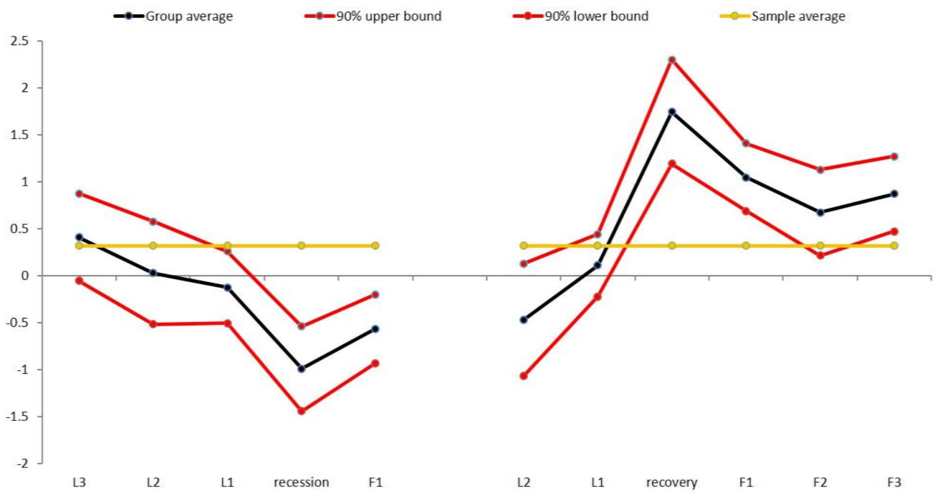
Quarterly growth rate %. Recession refers to the 1st quarter of recession according to NBER dating, recovery refers to the 1st quarter of recovery. L indicates the Lag operator, F the forward operator.

Figure 1b - ACTFP



Quarterly growth rate %. Recession refers to the 1st quarter of recession according to NBER dating, recovery refers to the 1st quarter of recovery. L indicates the Lag operator, F the forward operator.

Figure 2 - TFP



Quarterly growth rate %. Recession refers to the 1st quarter of recession according to NBER dating, recovery refers to the 1st quarter of recovery. L indicates the Lag operator, F the forward operator.

Table 1 presents the evidence to support stylized facts 2 and 3. The correlation coefficient between output growth and productivity growth, according to TFP, ATFP, ACTFP, and its 90% confidence interval are obtained. Regarding adjusted measures, it can be seen that during turning points the correlation is substantially higher than for the rest of the sample. Using ATFP, the correlation during turning points is 55.9% with a lower bound of 24.9%; for the rest of the sample the correlation is 12.9% with an upper bound of 23.1%. Similarly, using ACTFP, the correlation during turning points is 73.4% with a lower bound of 50.7%, whereas for the rest of the sample the correlation is 32.9% with an upper bound of 41.9%. Thus for both measures the correlation coefficient is significantly different. The 3rd stylized fact is reflected in the fact that for both ATFP and ACTFP the higher bound of the correlation for the rest of the sample is lower than the correlation during turning points, thus pointing to a significantly lower correlation. It can also be seen that the correlations are lower for the rest of the sample than for the overall sample. On the other hand, unadjusted TFP does not present any of the described patterns. The correlation with output during turning points is just slightly above the ones for the whole sample and for the rest of the sample.

Table 1 - Correlation output productivity by subsample

Correlation	Estimate	Lower B.	Upper B. (90%)
Whole sample (num obs 269)			
TFP	84.93	81.23	87.93
ATFP	19.23	9.33	28.73
ACTFP	40.03	31.23	48.13
Turning points (num obs 22)			
TFP	86.73	55.73	96.53
ATFP	55.93	18.03	79.43
ACTFP	73.43	50.73	86.53
Rest sample (num obs 247)			
TFP	83.33	79.03	86.73
ATFP	12.93	2.53	23.13
ACTFP	32.93	23.23	41.93

b) Robustness

b.1) Relative frequency

Having established the stylized facts one question immediately arises. Are the characteristics described for turning points uncommon? In other words, what is the probability that a set of points within the sample - other than at turning points - satisfies the 3 stylized facts? To answer this I carry out the following exercise. From the sample of growth rates of output I exclude turning points, and select two subsamples (low growth and high growth subsample) that replicate approximately the average GDP growth of Q1 of recession and recovery respectively. The high growth subsample consists of the 92 quarters with the highest GDP growth, and the low growth subsample of the 25 quarters with the lowest GDP growth[46], the number of observations in each subsample being selected to match observed GDP growth in Q1 of recovery and recession respectively.

Table 2 - Turning points and selected subsamples

Group	Period	Average Output Growth	Num obs
Turning Points	Recession	-4.45	11
	Recovery	7.75	11
Pools for Replication	Low	-4.52	25
	High	7.56	92

Annualized quarterly growth rates. Pools for replication refer to the two subsamples obtained targeting the average growth rate of GDP during turning points.

The following exercise is carried out. For each pool (the low and high growth groups) 11 observations are randomly chosen to achieve two subsamples of the same size of the recession and recovery groups[47]. For each subsample, a t statistic of the difference of

[46] In both cases turning points are excluded from the sample.

[47] I use the preselection step above in order not to exaggerate the scarcity of subsamples which satisfy the stylized facts. As adjusted productivity is moderately but positively correlated with output growth,

productivity growth between the group and the whole sample is computed. Then, both subsamples are pooled together and the correlation of productivity and output is computed. At each step, the statistic obtained is compared to the one corresponding to the recession and recovery groups. If the statistic obtained is equal to or greater in absolute value than the corresponding one in the turning points group, the case is deemed positive and counted. In addition, if the subsamples satisfy both the t statistic and the correlation coefficient criteria, they are counted separately. Therefore, the exercise quantifies the occurrences of the stylized facts 1 and 2[48], and thus estimates their relative frequency given the number of random samplings performed. The exercise is carried out for ATFP, ACTFP separately and combined; additionally, TFP is considered separately. The results in Table 3 are expressed as proportions. It can be observed that obtaining a random sample of adjusted productivity measures that satisfy the conditions that turning points do is rather unlikely to occur. The most restrictive exercise, the one that requires they satisfy all conditions for both types of productivity, delivers a frequency of 0.026%. Thus, only a very small proportion of the combinations satisfies all the conditions that turning points do. By contrast for TFP the relative frequency is much higher. In fact 13.2% of the sampled cases satisfy both conditions. From this exercise I conclude that the 3 stylized facts that hold for turning points are very rare within the sample, and that, consequently, the probability of such empirical patterns arising by chance is very small.

Table 3 - Relative frequency of turning points' productivity movements

Measures/Conditions	t-stat exceeds t.p.	r>=r(t.p.)	Both	Runs*
ATFP	0.03542	0.00283	0.00213	10,000,000
ACTFP	0.01583	0.00099	0.00052	10,000,000
Both Measures	.	.	0.00026	10,000,000
Comparison to TFP				
TFP	0.138	0.834	0.132	1,000,000

*Note: Low pool 4,457,400 combinations possible; High pool 53,752,237,906,276 combinations possible. In the second column the relative frequency of cases with a t statistic higher or equal than recoveries, and lower or equal than recession of the high and low growth pool are reported. In the third column, the relative frequency of cases with a higher correlation than the empirical one for turning points is reported. In the fourth column, the cases satisfying both conditions are reported. In rows, the cases of ATFP, adjusted ACTFP, both measures, and TFP are reported in order.

b.2) Extreme output movements

In this section, I consider the possibility that the results are a consequence of abnormally large output movements. This is not the case. GDP growth is not much higher in Q1 of recovery than in the following 3 quarters of recovery, or lower in Q1 of

selecting random samples of 22 and analyzing whether they comply with the stylized facts would not be a fair exercise. Since Q1 of recession is generally a low output growth period and Q1 of recovery is generally a high output growth period, it is expected to a certain extent (due to the positive correlation) that the growth of productivity will be lower and higher than average.

[48]Stylized fact 3 does not imply any substantial further filtering. In addition, it slows down the algorithm, therefore I choose to abstract from it in the analysis. Nonetheless, I have carried out the exercise with a smaller number of trials including the 3rd criteria, and it did not alter the results.

recession compared to Q2 of recession[49]. Table 4 presents evidence that suggests that the mechanism behind the effects observed during turning points is not related to the magnitude of GDP movements. The following exercise is performed. First, turning points are removed from the sample. Then, two groups of 11 are selected, each group constituting an extreme, either the slowest growth quarters or highest growth quarters. After that, I examine whether these 2 subsamples have similar properties to the turning points subsamples. Table 4a presents the correlations between output and productivity of the extremes subsample and the rest of the sample. In terms of ATFP, the correlation is substantially lower for the extreme group than for the rest of the sample, showing that extremes exhibit the opposite behavior to turning points. In terms of ACTFP, the correlation obtained is virtually the same. In table 4b the average growth rate of productivity by sub sample is presented. Only in 1 of the 4 instances does the extremes group present the same behavior as turning points. Overall, the groups composed of the extreme values of the sample -- turning points having been excluded -- do not present the same behavior as turning points with respect to adjusted productivity measures. On the other hand, for unadjusted productivity (TFP) the results point, indeed, to a significantly higher correlation during extreme periods than for the rest of the sample. Furthermore, consistent with this high correlation of TFP with output, the unadjusted productivity measure presents both a significantly higher and lower than average growth rate in the largest and smallest output growth groups respectively.

Table 4a - Correlations output-productivity during extreme growth periods

Correlation (dY,dA)	Estimate	Lower B. (90%)	Upper B. (90%)
Extremes (num obs 22)			
TFP	94.9%	87.8%	97.9%
ATFP	-15.0%	-48.4%	22.3%
ACTFP	40.6%	5.4%	66.9%
Rest sample (num obs 225)			
TFP	80.1%	75.1%	84.2%
ATFP	24.1%	13.5%	34.2%
ACTFP	38.4%	28.6%	47.4%

Table 4b - Mean comparison test of productivity growth by extreme growth groups

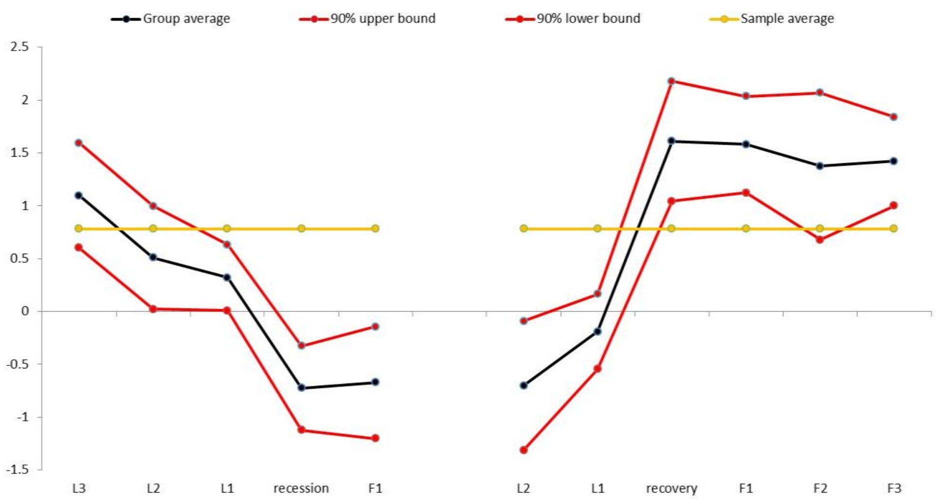
Measure	Group	Average group	Average rest	p-value	different s.d.
TFP	smallest	-5.04	1.55	0.00	no
	largest	7.86	0.99	0.00	no
ATFP	smallest	1.58	1.28	ns	no
	largest	0.87	1.31	ns	no
ACTFP	smallest	-0.08	0.88	ns	no
	largest	2.15	0.78	0.02	yes

[49]Figure 3 presents GDP growth rate around turning points and compares them to the rest of the sample. As can be seen, Q1 of recession tends to be low, and Q1 of recovery high, but without presenting exceptional growth.

b.3) Related variables behavior

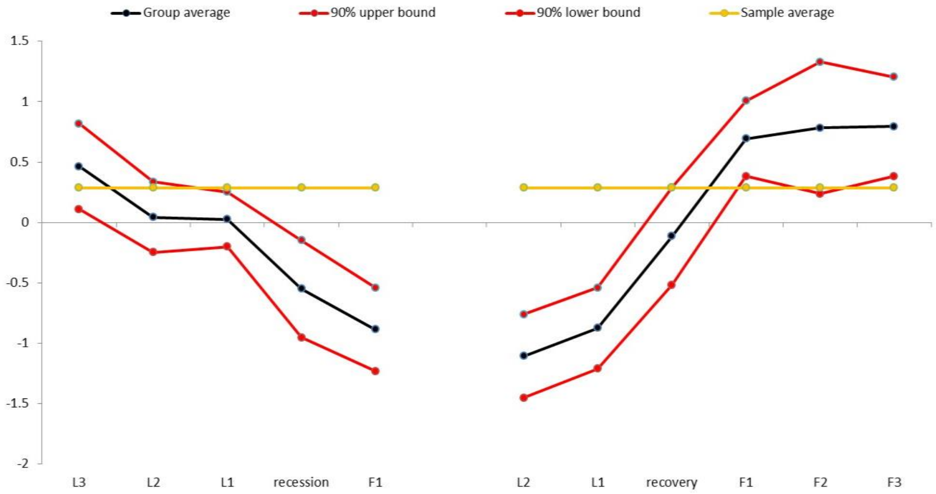
In this section, I consider whether the behavior of productivity during turning points is exceptional when compared to closely related variables, such as output or employment. To answer it, I analyze the growth rate of GDP, employment, hours, utilization, and utilization in the consumption sector. Figure 3 shows the results for GDP. Both Q1 and Q2 of recession are periods of lower than average growth. Recoveries present a similar pattern for a longer horizon. Q1-Q4 of recovery present higher than average growth, with small differences between quarters. It is worth highlighting the contrast with TFP, and especially with ATFP and ACTFP, where the unusual growth rates only last for one quarter, whereas GDP presents persistent behavior. Figures 4 and 5 analyze the behavior of labor input, in the first case hours worked and in the second workers. The overall pattern is clear, with strong declines in Q1 and, in particular, Q2 during recessions, a small decline during Q1 of recovery, and strong growth for Q2-Q4 of recovery. Of course, it is this behavior of labor input combined with that of output - strongest growth in Q1 of recovery and strongest decline in Q1 of recession - which leads to the unusual productivity movements. Figures 6 and 7 examine the utilization growth rate for overall production and for consumption sector production. As can be seen, the movements of utilization tend to be quite persistent and similar to those of GDP, with turning points presenting no unusual behavior. It can, therefore, be concluded that the stylized facts described are unusual in the sense that there is a lack of similar movements of related variables during the same periods.

Figure 3 - GDP



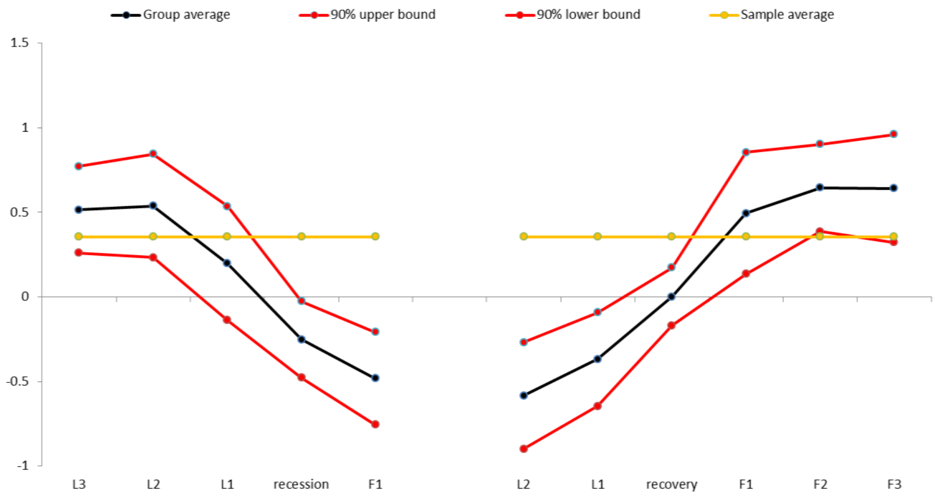
Quarterly growth rate %. Recession refers to the 1st quarter of recession, according to NBER dating; recovery refers to the 1st quarter of recovery. L indicates the Lag operator, F the forward operator.

Figure 4 - Hours



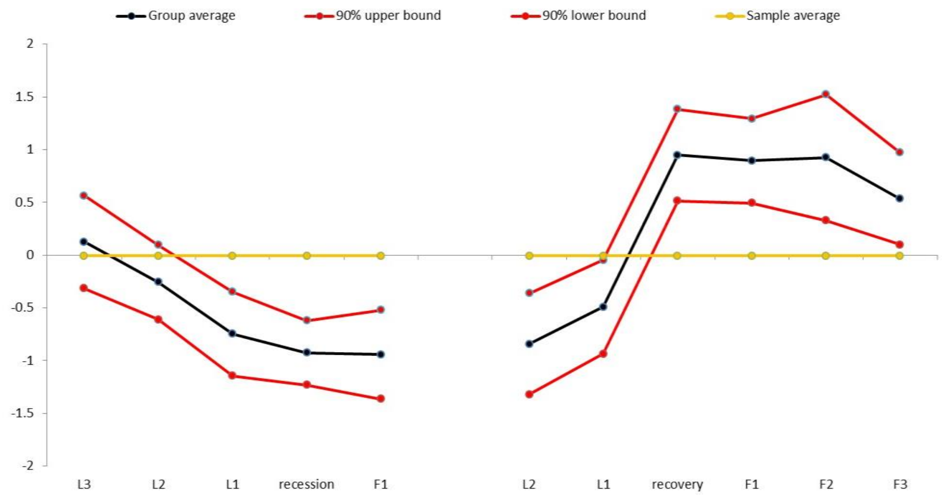
Quarterly growth rate %. Recession refers to the 1st quarter of recession, according to NBER dating; recovery refers to the 1st quarter of recovery. L indicates the Lag operator, F the forward operator.

Figure 5 - Employment



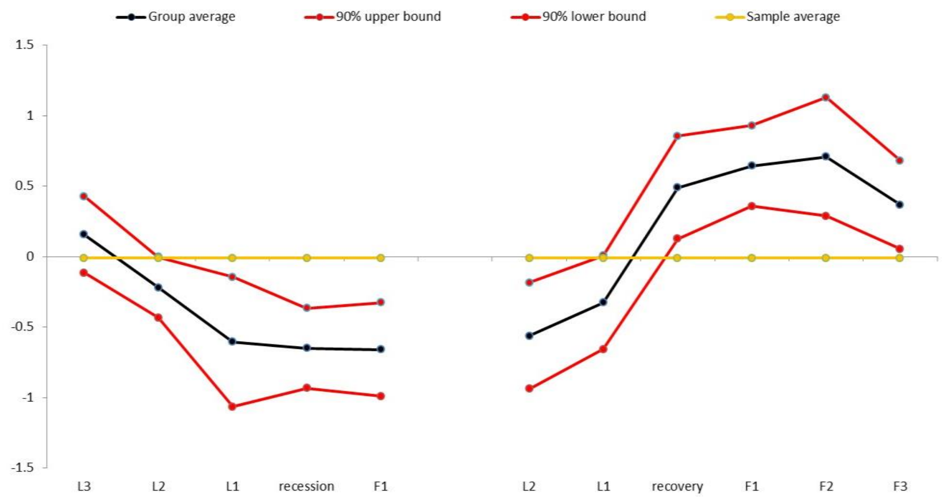
Quarterly growth rate %. Recession refers to the 1st quarter of recession, according to NBER dating; recovery refers to the 1st quarter of recovery. L indicates the Lag operator, F the forward operator.

Figure 6 - Utilization



Quarterly growth rate %. Recession refers to the 1st quarter of recession, according to NBER dating; recovery refers to the 1st quarter of recovery. L indicates the Lag operator, F the forward operator.

Figure 7 - Utilization in consumption sector



Quarterly growth rate %. Recession refers to the 1st quarter of recession, according to NBER dating; recovery refers to the 1st quarter of recovery. L indicates the Lag operator, F the forward operator.

b.4) The Great Moderation

The debate over structural changes before and during the great moderation is of relevance to the described stylized facts in two manners. First, regarding jobless recoveries after the most recent recessions, or slow recoveries as in Galí, Smets, and Wouters (2012). And second, regarding the reduction of procyclicality of productivity, see for instance Galí and Van Rens (2010) and McGrattan and Prescott (2012). With respect to the first topic it is of interest to answer if the behavior of productivity growth during the first quarter of recovery has changed since entering in the Great Moderation[50], as a change in employment growth during recent recoveries has been of

[50]For the purposes of this section I include the great recession of 2008 and its aftermath in the Great Moderation period.

much interest. To answer this first question I test whether Q1 of recovery is significantly different for the last 3 recessions - compared to the other 8 post war recessions - in several variables of interest. Table 5 presents the p-values of t tests. I find that Q1 of modern recoveries are periods of slow growth, and not exclusively jobless growth, in other words both output and hours worked are significantly lower in Q1 of modern recoveries, both with a p value of 0.04. The behavior of productivity however is not significantly different from the rest of the sample, this is true for TFP, ATFP, ACTFP. In addition to the t-tests, due to concerns regarding the sample size, I add the Mann-Whitney test. Because it is nonparametric, the test is in principle well suited for a small number of observations. As can be seen, it also indicates that the differences, whilst significant in output and hours, are not in any of the TFP measures.

Table 5 - Comparison of Q1 of recovery Great Moderation and rest of the sample, growth rate of variables of interest

Alternative Hypothesis	p-value (t-test)	p-value (Mann-Whitney)
Output growth smaller	0.04	0.02
Hours growth smaller	0.04	0.03
TFP growth smaller	0.17	0.16
ATFP growth smaller	0.36	0.34
ACTFP growth smaller	0.43	0.50

A comparison of the growth rate of selected variables of interest during Q1 of recovery in the Great Moderation and the rest of the post-war sample. Two tests (t-test and Mann-Whitney test) are used and their associated p-value/p-values reported. The alternative hypothesis of the test, which would not be rejected at the 10% level for p-values below 0.1, is that the variable of interest presents a lower growth rate for the Q1 of recoveries belonging to the Great Moderation.

Regarding the relationship with the second topic, the reduction of the procyclicality of productivity during the Great Moderation (GM), it would be interesting to examine whether the reduction observed for unadjusted productivity is present for ATFP or ACTFP, and to observe what role turning points play in this setting. Table 6 presents the correlations of TFP, ATFP, and ACTFP, subsampled by period (GM or before) and type of period (turning points or rest of the sample). TFP growth rate, presents a 87.6% correlation with output growth before the GM, and 73.8% afterward. By contrast, ATFP and ACTFP present the opposite trend, with the correlation increasing 8 and 4 percentage points respectively during the Great Moderation. Taking only turning points into consideration, the correlation of TFP does not vary before and during the GM. Consequently, the decrease in overall correlation can be attributed to quarters that are not turning points. The increase in correlation for adjusted productivity measures, on the other hand, is observed both during turning points and in the rest of the sample. In general, stylized facts 1, 2 and 3 hold for both subperiods.

Table 6 - Correlations output-productivity by period and subsample

Period	Selection	Measure	Correlation (3)	Num obs
GM	All	TFP	73.8	105
		ATFP	24.4	105
		ACTFP	42.0	105
pre GM		TFP	87.6	164
		ATFP	16.8	164
		ACTFP	38.5	164
GM	Turning Points	TFP	95.9	6
		ATFP	78.7	6
		ACTFP	96.0	6
pre GM		TFP	95.7	16
		ATFP	54.4	16
		ACTFP	72.5	16
GM	Rest of the sample	TFP	74.7	99
		ATFP	21.1	99
		ACTFP	39.9	99
pre GM		TFP	85.8	148
		ATFP	9.0	148
		ACTFP	28.9	148

b.5) Inter- and intra-sectoral reallocation

One potential source of productivity movements is reallocation between sectors or firms. In this section, I analyze this issue. However, one important limitation is the lack of a quarterly frequency for disaggregated data. Nevertheless, this limitation is unlikely to affect the results shown here, since it is plausible that reallocation effects have a higher impact on lower frequencies such as in Caballero and Hammour (1994) rather than on the quarterly frequency. Using this hypothesis, the annual results of this section regarding reallocation can be interpreted as an upper bound for such effects on the quarterly frequency.

To enquire into intersectoral reallocation, I use the NBER-CES manufacturing database 1962-2009. This includes total factor productivity obtained using labor, capital, materials and energy. I then decompose TFP growth in a between and within component:

$$within_t = \frac{\sum_{\forall i}(tfp_{it} - tfp_{it-1})s_t}{tfp_{t-1}}; between_t = \frac{\sum_{\forall i}(s_{it} - s_{it-1})tfp_{it-1}}{tfp_{t-1}}$$

where s , is the employment share. Within growth is the weighted sum of idiosyncratic productivity growth, and between growth the contribution of changes in employment shares to overall growth keeping idiosyncratic productivity constant. Figure 8 presents the results, plotting TFP growth and the contribution of within growth. As can be seen, the movements of productivity are mainly caused by the within component, and reallocation only contributes marginally. Table 7 presents the same exercise used as in aggregate productivity above, taking the within component of productivity into consideration. Recessions are identified as the 1st year of negative shipments growth, and recoveries as the 1st year of positive growth after a recession. As can be seen, the results hold. It must be emphasized, however, that in this case TFP is not adjusted for utilization. Nonetheless, given the small role of inter-sectoral reallocation, it can be ruled out as a potential source of the stylized facts.

Figure 8 - TFP growth and Within TFP growth, Sector level data

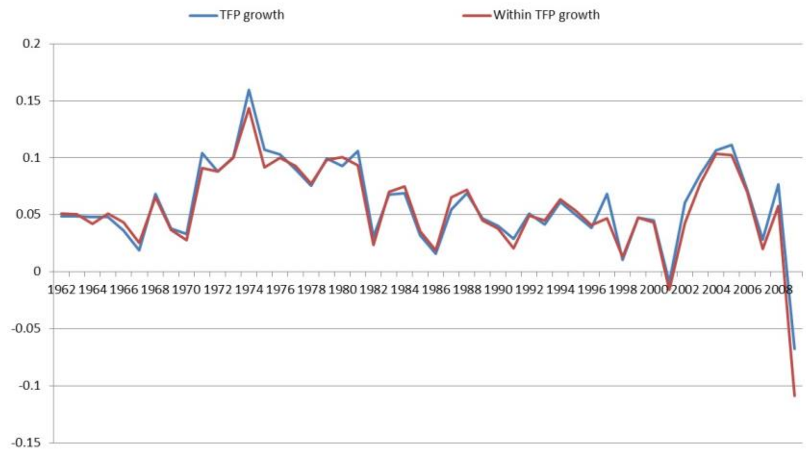


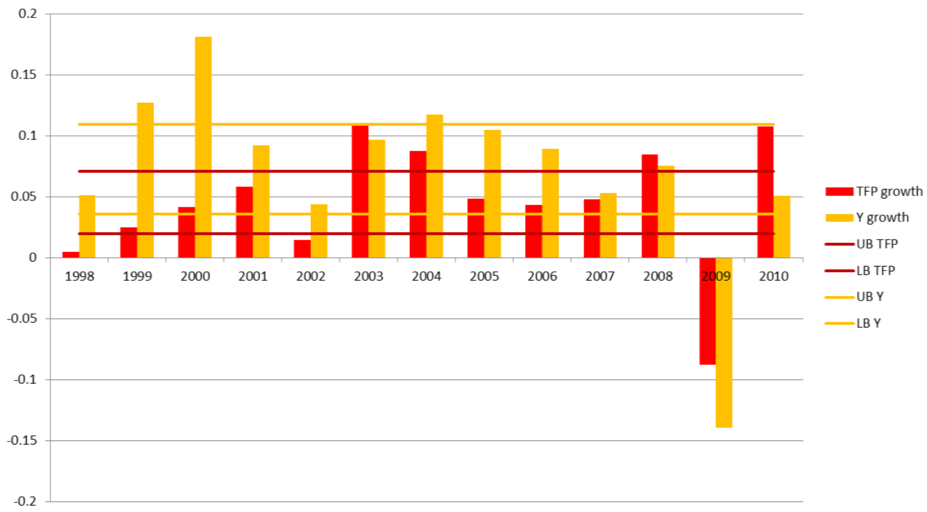
Table 7 - Differences across turning points, within contribution, Sector level data

Group	Observations	Average
Rest Sample	42	0.025
"Recessions"	6	-0.017
Rest Sample	43	0.019
"Recoveries"	5	0.028
Difference: Rest - "Recessions"		0.042
Ha: diff>0	p-value	0.013**
Difference: Rest - "Recoveries"		-0.009
Ha: diff>0	p-value	0.048**

I also consider the case of reallocation between firms, instead of sectors. To this end, I use a Compustat sample. As a proxy for TFP, Sales over Employment is used. Figure 9 presents the yearly growth rate of Sales and TFP, and the upper and lower 90% confidence intervals. In 2009 and 2010, a clear drop in Sales followed by a recovery can be observed. Simultaneously, the proxy for TFP follows the clear procyclical spikes found in aggregate productivity, with 2009 TFP being below the lower bound of the interval, and the 2010 TFP being above the upper bound. Figure 10 presents the decomposition of within and between productivity growth, as in the case of intersectoral reallocation. Additionally, the extensive margin is included in the analysis. The entrants' contribution to TFP is obtained by assigning 0 TFP in the year before entry, thus making it positive by construction. The contribution of exiting firms is obtained by assigning 0 TFP in the year after exit. With this construct, aggregate TFP growth can be decomposed into within, between, entry and exit components. It can be observed that the movements of TFP in 2008 and 2009 are mainly caused by the within component.

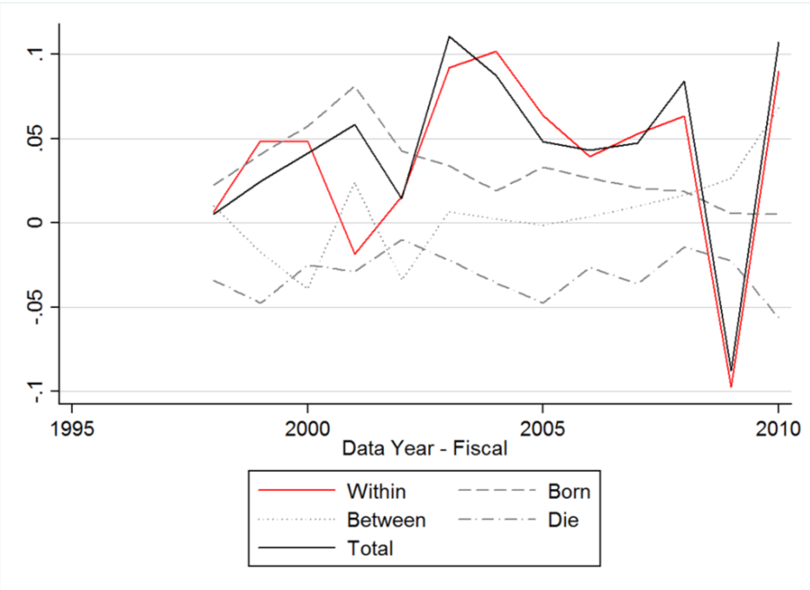
Thus, reallocation - whether across firms or sectors - does not appear to be a plausible mechanism to explain the high frequency aggregate productivity movements.

Figure 9 - Productivity and Output growth. Firm level data



Productivity proxied by sales per employee. Growth rates.

Figure 10 - Decomposition of contribution productivity growth. Firm level data



Contribution to growth rates, and Total growth rate

c) Discussion of empirical findings

From the analysis in this section, the importance of the stylized facts in the debate over the role of technology in business cycle is established.

First, the procyclical spikes of adjusted productivity precisely at turning points have been shown, to be neither a consequence of comovements with related variables, nor due to turning points being exceptional periods in any other sense than their definition and the behavior of adjusted productivity. Random chance, extreme output movements, or reallocation effects are also unlikely to be the cause of the spikes. Moreover, the spikes in productivity during the start of recovery are present during both the Great Moderation and the previous period.This is remarkable as both output and employment change their behavior significantly; productivity, however, and adjusted productivity, in particular, do not. The presence of the procyclical adjusted productivity movements just during turning points can be of great importance in understanding the main component of business cycle dynamics, recessions, and the first few quarters of recovery. Indeed, adjusted productivity growth from Fernald (2012) is one of the best proxies for quarterly technological change that are available. Having the procyclical spikes interpreted as exogenous technology shocks could, with the right model, plausibly result in a recession being started by a negative technology shock, and, in turn, being ended by a positive technology shock that starts the recovery process.

Second, stylized facts 2 and 3 are also of substantial importance regarding the role of technology in the business cycle. Indeed, the fact that correlation is much higher during turning points than during the rest of the sample implies that measures that focus on the overall sample to obtain technology-output correlations might be underestimating its role in the most crucial quarters of the business cycle.

Overall, the conclusion of this section is that the stylized facts presented do not appear to have a mechanical explanation to justify them, and that the cause is a topic well worthy of further research.

3.5 Source of the of the adjusted productivity movements during turning points

In this section, I investigate possible sources of the adjusted productivity movements during turning points. Given the precise timing of the productivity movements and the high correlation of productivity and output during turning points, the source of the stylized facts might have a large impact on the role of technology shocks in the business cycle. I present here the first attempt at establishing the cause, although this topic will require further investigation. To study the issue, I first postulate the hypothesis that the stylized facts could be caused by technology shocks. Then I turn to a competing hypothesis which holds that the stylized facts are a consequence of demand influence on adjusted productivity. This goal goes beyond simple curiosity, given the particular quarters when the productivity movements occur (during turning points). If caused by technology shocks, these could be the cause of recessions and recoveries and thus of much of the output variation at business cycle frequencies. Technology shocks, being exogenous, are unlikely to occur precisely during turning points by random chance, which suggests that a causal link can be a more likely hypothesis. By contrast, if demand influences the adjusted measures of productivity during turning points, it could be that either demand shocks are driving the results, and thus that there is a causal between demand and the business cycle, or that some third shock influences demand and, in turn, adjusted productivity.

a) Technology shocks

In this section I analyze the possibility that the procyclical spikes described above are caused by technology shocks in standard models, in particular an RBC model and a NK model. The concrete objective is to test whether in such standard models a technology shock that mimics the observed movements of adjusted productivity is capable of generating the empirical behavior of output. Given that the present study concerns quarterly data, it is natural to use a model with price and wage stickiness, such as the one described in Galí (2011). However, to illustrate that the results do not derive exclusively from the mechanisms involved in a NK model, I run a comparable exercise with a standard RBC model. The models are described in detail below.

a.1) An RBC model

The model follows the Dynare specification of Johannes Pfeifer[51]. The model I use is a standard RBC with the following variables:

Meaning	Variable
Output	Y
Consumption	C
Capital	K
Labor	L
Technology	Z
Investment	I

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The following equations describe the model; note that the parameters will be defined later. Notice that for a given technology path, the equations completely describe the solution.

Labor Supply decision:
$\frac{\varphi C_t}{1-L_t} = (1-\alpha) Z_t \left(\frac{K_t}{L_t}\right)^{\alpha}$
Euler equation
$\frac{1}{C_t} = E_t \left\{ \beta \frac{Z_{t+1}}{C_{t+1}} \alpha \left(\frac{K_{t+1}}{L_{t+1}}\right)^{\alpha-1} + (1-\delta) \right\}$
Capital LOM
$K_t = I_t + (1-\delta) K_{t-1}$
Cobb-Douglas Production Function
$Y_t = K_t^{\alpha} L_t^{1-\alpha}$
Accounting identity
$I_t = Y_t - C_t$

Following the structure of the model, there are two types of parameters; the ones that are exogenously determined and the ones that follow from a combination of other parameters.

Meaning	Parameter	Value
Depreciation rate	*δ*	*i_y/ k_y*
Discount	*β*	1/(*α/ k_y*+(1- *δ*))
Inverse Frisch Elasticity	*φ*	(1- *α*) (*k_ss/ l_ss*)^ *α* (*1-l_ss*)/ *c_ss*
Capital in steady state	*k_ss*	((1/ *β*-(1- *δ*))/ *α*^(1/(*α* -1))) *l_ss*
Investment in steady state	*i_ss*	*δ k_ss*
Labor in steady state	*l_ss*	0.33
Capital Exponent	*α*	0.33
Investment to output ratio	*i_y*	0.5
Capital to output ratio	*k_y*	10.4
Technology persistence	*ρ*	0.97

a.2) A NK model

The model follows the Dynare specification that implements the Basic New Keynesian model from Galí (2011)[52]. The notation follows the convention of x denoting the log of the variable X, thus $x = \log(X)$, except for variables that indicate changes from the previous period (such as inflation) or deviations from a baseline (such as the output gap). The variables are:

Meaning	Variable
Wage inflation	π_w
Price inflation	π_p
Natural rate	r^n
Technology	z

[52]The script in question was developed by Richard Horne and Roger Gomis.

Taylor rule wedge	ν
Nominal interest rate	i
Output gap	$\tilde{y}$
Wage gap	$\widetilde{w}$
Natural Wage	w^n
Natural Output	y^n
Output	y
Labor force	l
Unemployment	u
Employment	n
Wage	w
Real rate	r^r

The equations that define the model are described below, followed by the parameters used:

Natural wage
$w_t^n = z_t(1-\alpha(1+\psi)/\upsilon)/(1-\alpha)$
Natural rate
$r^n = \rho + \sigma \cdot \frac{(1+\psi)}{\sigma(1-\alpha)+\psi+\alpha} \cdot E_t\{z_{t+1} - z_t\}$
Forward looking price inflation equation
$\pi_t^p = \beta E_t \pi_{t+1}^p + \kappa^p\ \tilde{y}_t + \lambda^p\ \widetilde{w}_t$
Forward looking price wage equation
$\pi_t^w = \beta E_t \pi_{t+1}^w + \kappa^w\ \tilde{y}_t + \lambda^w\ \widetilde{w}_t$
Euler equation, in output gap terms
$\tilde{y}_t = E_t\left\{ \tilde{y}_t - \frac{1}{\sigma}\left(i_t - \pi_{t+1}^p - r^r\right)\right\}$
Unemployment
$u_t = \dfrac{\widetilde{w}_t - \left(\sigma + \frac{\psi}{1-\alpha}\right)\tilde{y}_t}{\psi}$
Wage gap evolution
$\widetilde{w}_t = \widetilde{w}_{t-1} + \pi_t^w - \pi_t^p - (w_t^n - w_{t-1}^n)$
Taylor rule
$i_t = \rho + \phi^\pi \pi_t^p + \phi^y y_t$
Output gap definition
$\tilde{y}_t = y_t - y_t^n$
Natural output
$y_t^n = z_t \frac{1+\psi}{\upsilon}$
Wage gap definition
$\widetilde{w}_t = w_t - w_t^n$
$r_t^r = i_t - \pi_{t+1}^p$
Labour force participation
$l_t\psi = w_t - \sigma y_t$
Employment
$n_t\psi = w_t - \sigma y_t - \psi u_t$

The parameters finally read[53]:

Parameter	Definition
λ^w	$\frac{(1-\theta^w)(1-\beta\theta^w)}{\theta^w(\sigma+\varepsilon^w\psi)}$
λ^p	$\frac{(1-\theta^p)(1-\beta\theta^p)}{\theta^p(1-\alpha)/(1-\alpha+\alpha\varepsilon^p)}$
κ^w	$\lambda^w\left(\sigma+\frac{\psi}{1-\alpha}\right)$
κ^p	$\lambda^p \ \frac{\alpha}{1-\alpha}$
υ	$(\sigma-1)(1-\alpha)+\psi+1$
M^w	$\frac{\varepsilon^w}{\varepsilon^w-1}$
M^p	$\frac{\varepsilon^p}{\varepsilon^p-1}$
β	0.99
α	0.25
ε^p	9
θ^w	0.75
θ^p	0.75
ρ	-ln(0.99)
ψ	5
ε^w	4.52
φ^p	1.5
ϕ^y	0.125
σ	1

a.3) Technology shock specification and results

In both models technology follows:

$$z_t = \varepsilon_t + \varepsilon_{t-1} + \varepsilon_{t-2} - z_{t-3}$$

where z_t represents the log of the variable, and ε_t is an impulse, with the first impulse being different than zero $\varepsilon_0 = k$, and the rest being zero $\varepsilon_t = 0 \ \ \forall t > 0$. This is the only unusual element in otherwise perfectly standard NK and RBC models[54]. The process differs from the standard in order to replicate the observed movements of adjusted productivity (a proxy measure for technology), creating a switching or cyclical pattern.

Figure 11a describes the deviation of growth rate of technology from the sample average in the RBC and NK models, contrasting it to the empirical average behavior of AP (ACTFP, in particular, since its procyclical spikes are more clearly observed). The comparison is made at Q1 and Q2 of both recession and recovery. It can be seen that the simulated technology matches the empirical data in Q1 of recession. This is unsurprising given that the impulse has been calibrated to match it - and to do so qualitatively in Q1 of recovery. Moreover, the simulated shock matches the behavior of adjusted productivity in Q2 of both recession and recovery, suggesting that the law of motion is a suitable candidate for the current exercise.

The results for output are presented in figure 11b. For the RBC model it can be seen that

[53] The notation follows Galí (2011).

[54] In a standard simulation the TFP process would typically be assumed to follow $z_t = \rho z_{t-1} + \varepsilon_t$, $\varepsilon_0 = k$, and $\varepsilon_t = 0 \ \ \forall t > 0$ with ρ indicating its persistence.

the contemporaneous response to the shock in turning points is comparable to its empirical counterpart, suggesting that the model does not need any additional amplification beyond its standard version[55]. By contrast, the response of output in the NK model is substantially below its empirical counterpart. The intuition for this divergence is straightforward. As only a small share of firms are able to respond to the technology shock by adjusting prices, output has to respond to a much lesser degree than in a flexible price model.

With respect to Q2 of both recession and recovery, it is clear that neither the RBC nor the NK model can replicate qualitatively the response of output observed empirically. This is due to insufficient propagation. There are some effects on output after a lag of one period but they are negligible, particularly compared to the original movement of both productivity and output in the previous period.

These results suggest that in standard DSGE models, technology shocks cannot generate the observed behavior of output and adjusted productivity. Therefore, to the extent that one has confidence in the standard models, this serves as a strong argument against technology shocks being the cause of the adjusted productivity movements during turning points. As mentioned above, given their exogenous nature, it would be unusual to find technology shocks occurring during turning points unless they were the cause of such turning points. The argument is simple: shocks are by definition independent and given that only 8% of the quarters in the sample are turning points, the chance of an independent technology shock occurring in the required size during a turning point at random is small. If, on the other hand, the independent realization of the shocks causes the turning points, then the coincidence is tautological.

[55]In fact, for Q1 of recovery the model presents an *excess* of amplification.

Figure 11a - Technology growth rate (deviations from the average) DSGE models and data

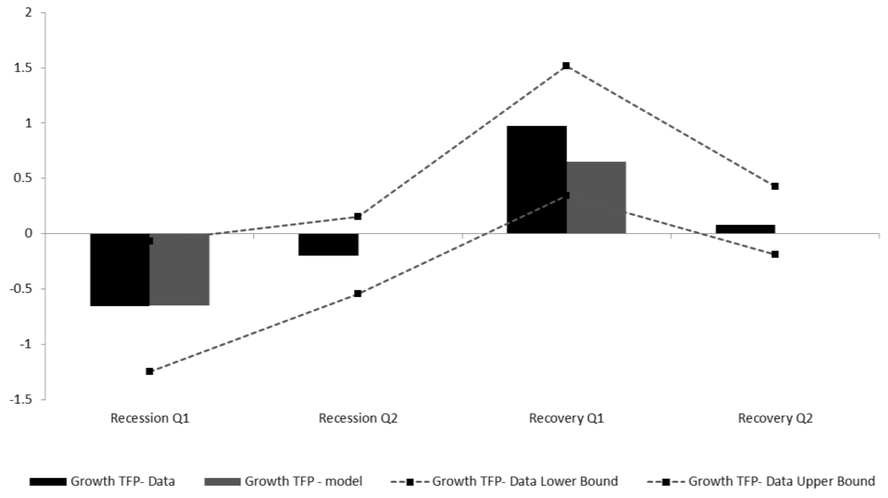
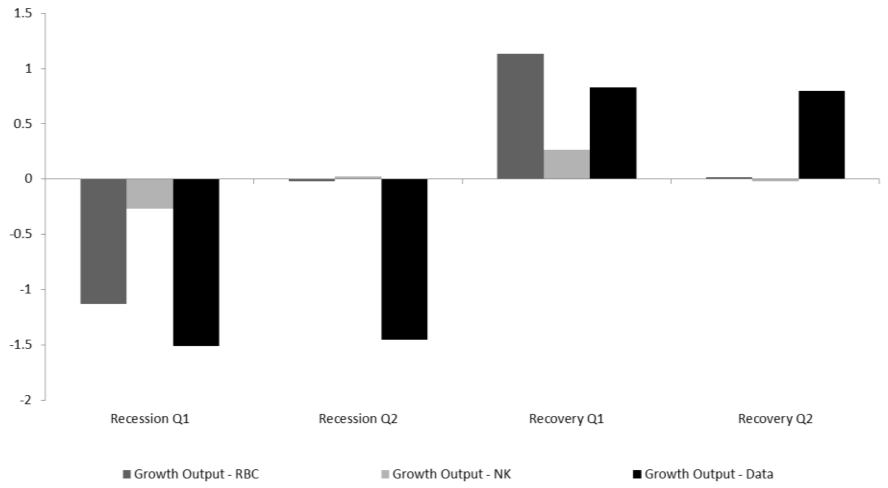


Figure 11b - GDP growth rate (deviations from the average) DSGE models and data



b) Demand influence on adjusted productivity

In this section the possibility that demand influences adjusted productivity is considered. In this case, the observed movements of adjusted TFP during turning points would represent an endogenous response to demand changes occurring at precisely the start and end of recessions.

b.1) Possible mechanisms of demand influence in adjusted TFP

That demand, or demand shocks, can affect measured TFP is well established in the literature. It is not so clear, however, how demand can influence adjusted TFP. To give a simple example, straightforward labor hoarding in response to a demand shock does not show up in adjusted measures of productivity.

In order for demand to affect adjusted productivity it is necessary that inputs, for which there is slack, be used in activities that (1) require the use of such inputs in the intensive margin (hours of work devoted or functioning hours of equipment) and (2) are not included in output measures. Furthermore, in order to be relevant to the present study, these activities should at least be plausibly responsive to demand or, at the very least, to the business cycle condition. With no claim to being exhaustive, I suggest some plausible candidates and related studies that satisfy the above conditions.

Bernard and Okubo (2016) show that when there is slack available, there is more product switching, i.e. the creating of new products and the retiring of old ones. Moreover, there are input costs in the intensive margin in making such changes that do not directly translate to output in the present period. Therefore, productivity, even if it is adjusted to the degree of utilization of inputs, can vary, while at the same time the technology used for production remains unchanged. McGrattan and Prescott (2012) suggest that intangible investment is responsible for the weakening of output -labor productivity correlation, this type of investment would not show up in productivity measures, but requires inputs in the intensive margin. Bellmanna, Gerner and Leber (2013) examine the issue of firm-provided training during the great recession, some on the job training activities require the use of the intensive margin of labor (work hours) without being accounted for in output terms. Finally, perhaps more indirectly related, Nickell, Rollins and Hellman (2012) and Volden and Wiseman (2015) present evidence suggesting that the great recession affected how firms allocated resources to non-market projects such as developing a relationship with clients in financial difficulties or lobbying activities.

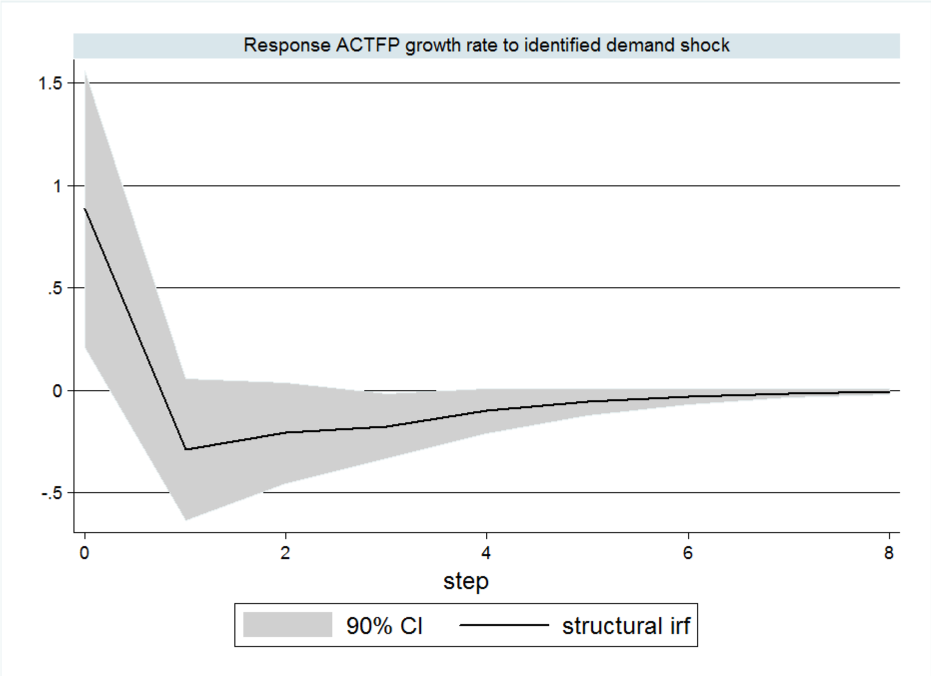
b.2) SVAR Evidence

An interesting piece of evidence can be obtained using a SVAR model with long run restrictions. A natural choice is to consider an SVAR model with adjusted productivity and hours in growth rates to identify demand shocks as those without permanent effects on technology[56], following Blanchard and Quah (1989) and Galí (1999). Afterwards, I obtain the response of technology to these. It is worth emphasizing that the restriction used is that the cumulative impact of the demand shock has to be zero, but no particular horizon to accomplish this is assumed. Since ACTFP presents the clearest evidence during turning points, I use its growth rate as the measure of productivity. The results are plotted in Figure 12: demand seems to affect transitorily (during just 1 quarter) technology in a positive fashion. Afterwards, the response entails a declining negative impact that is barely significant. The one quarter response of adjusted productivity to a demand shock is compatible with the stylized facts and is not a mechanical consequence of the identifying assumption[57].

[56]This methodology leaves the door open to the confusion of transitory technology shocks with demand shocks. I address this issue immediately after presenting the results.

[57]For instance, in Galí (1999) the response of TFP to a demand shock, identified with a similar methodology, presents a positive point estimate during four quarters.

Figure 12 - SIRF ACTFP growth rate response to a demand shock



Confidence bands obtained by bootstrap (200 replications). Step units: quarter. Response obtained with a model of 2 lags.

I consider now whether accounting for the influence of the identified demand shocks on ACTFP during turning points results in the stylized facts not holding up anymore. The answer is that the stylized facts do not hold up. To account for the influence of the demand shock during turning points, I construct a modified measure of ACTFP, labeled mod(ATFP), that is orthogonal to the identified demand shocks during turning points. The new measure is simply:

$$\text{mod}(ACTFP_t) = ACTFP_t \qquad \text{rest sample}$$

$$\text{mod}(ACTFP_t) = ACTFP_t - \varepsilon_t \theta \qquad \text{turning points}$$

where ε_t is the estimated demand shock, and θ the OLS coefficient of regressing ACTFP against the demand shock. Therefore, by construction, the correlation between the demand shock and the modified productivity is 0 during turning points. The two tables below show the analysis of the stylized facts for this new measurement. As can be seen, none of the stylized facts hold up, anymore. The growth rate of the modified productivity is not different in turning points than the rest of the sample at usual significance levels. Furthermore, the correlation with output, is not larger during turning points, anymore. In fact, the point estimate of the correlation coefficient lies below both the overall sample and the rest of the sample ones[58].

[58]The fact that the stylized facts do not hold up anymore is not a mechanical consequence of the identification scheme of the demand shocks. In particular, the procedure does not entail (in principle or in practice) the filtering out of ACTFP movements at the quarterly frequency.

Table 8 - $mod(ACTFP_t)$ growth around recessions

Period	Average group	Average rest	p-value	Different s.d.
Recession	-0.87	0.83	ns	yes
Recovery	0.86	0.77	ns	no

t tests of averages across group. Null hypothesis no difference.

Table 9 - Correlation output- $mod(ACTFP_t)$ by subsample

Measure	Subsample	Estimate	Lower B. (90%)	Upper B. (90%)
mod(ACTFP)	Whole sample	32.1%	22.8%	40.8%
	Turning Points	25.9%	-11.2%	56.7%
	Rest Sample	32.9%	23.2%	41.9%

One could argue that this result is consistent with transitory technology shocks[59], instead of demand shocks. Aside from the surprising duration of the postulated technology shocks, a further argument weakens the case for technology shocks being able to explain the evidence above. In particular, I follow a similar methodology to the one that Francis and Ramey (2005) used to enquire whether the technology shocks identified by Galí (1999) using long run restrictions were indeed plausible exogenous technology movements. The basic idea of the authors was to check whether the identified shocks were independent of several other identified shocks. In the context of this article, the test that I propose is to check whether the short run shocks identified are associated with the identified monetary policy shocks of Romer and Romer (2004). In particular, a global test of significance (F test) is used. For completeness, the results are compared with the SVAR identified permanent shocks. Table 10 reports the results. As it can be seen, both during turning points and for the whole sample, the shocks identified as having a permanent effect on technology are consistently not significantly affected by the monetary policy shocks. By contrast, the shocks identified as having a short run effect on technology are in all cases significantly affected by monetary policy shocks. Therefore, it can be concluded that the transitory shocks identified using the SVAR scheme cannot plausibly be considered technology shocks.

Table 10 - F test p-value

Effect of the shock	Subsample	MP (t)	MP (t,...,t-3)	MP (t-1,...,t-4)
Long run	Whole sample	0.55	0.93	0.88
Short run		0.039**	0.023**	0.03**
Long run	Turning Points	0.46	0.16	0.10
Short run		0.042**	0.04**	0.03**

F test of global significance by type of period and shock.

b.3) Relation to plausible demand indicators

b.3.1) Relation to Manufacturing Sector Orders

[59]The technology shocks required in this case are extremely short lived, as they would only affect (positively) productivity for one quarter.

In this section I use one of the OECD manufacturing business tendency[60] indices as a demand indicator, in particular the Order books tendency indicator. The index simply factors in the answers to the question : "How have your orders developed over the past 3 months? They have ... + increased = remained unchanged - decreased". Thus a positive score denotes that more firms are reporting an increase in orders than a decrease; therefore, the indicator is the net percentage of firms reporting an increase in orders. This magnitude is reasonably related to demand, and given the quarterly frequency, price stickiness can play an important role in weakening any link of this measure to technology shocks. As with all variables in this study, I take into consideration the quarterly variation in the variable[61]. It should be noted, however, that the growth rate cannot be used as the indicator can be both positive and negative. Table 11 presents the changes around turning points, comparing them to those of the rest of the sample. The patterns are quite similar to ATFP and ACTFP, with the exception of a positive uptick for the second quarter of recession. Table 12 presents the correlation between adjusted productivity and the demand side indicator. As can be seen, the point estimate of correlation is substantially higher during turning points.

Table 11 - Manufacturing sector orders changes around recessions

Period	Average group	Average rest	p-value	different s.d.
Recession	-9.22	0.39	0.07*	yes
Recession F1	5.77	-0.21	0.09*	no
Recovery	28.7	-1.13	0.00***	no
Recovery F1	0.88	-0.01	ns	no
Recovery F2	-2.3	0.11	ns	no
Recovery F3	0.88	-0.01	ns	no

Level quarterly change of OECD manufacturing business tendency for the US; as the index takes positive and negative values, the growth rate is avoided.

Table 12 - Correlation productivity demand indicator by subsample

Correlation (di,dA)	Subsample	Estimate	Lower B. (90%)	Upper B. (90%)
ATFP	Whole Sample	7.7%	-5.2%	20.4%
	Turning points	47.3%	0.8%	77%
	Rest Sample	0.3%	-13.1%	13.7%
ACTFP	Whole Sample	25.8%	13.4%	37.4%
	Turning points	67.8%	30.9%	87.0%
	Rest Sample	14.0%	0.6%	26.9%

Demand indicator (di): Level quarterly changes of OECD manufacturing business tendency for the US

b.3.2) Relation to Consumer Confidence Indicator

In this section, I use the University of Michigan Consumer Sentiment Index. Consumer sentiment is reasonably related to demand, and at the quarterly frequency it is rather

[60]Business Tendency Surveys for Manufacturing: Confidence Indicators: Composite Indicators: European Commission and National Indicators for the United States.
[61]To match the appropriate frequency the variable used is the quarterly average of the three months composing the quarter.

implausible to claim that it responds to technology shocks. As with all the variables in this study, I take into consideration the quarterly variation in the variable[62]. I use the difference instead of the growth rate for comparability with the previous indicator. Table 13 presents the changes around turning points, comparing them to those of the rest of the sample. The patterns are quite similar to ATFP and ACTFP, with the exception of a positive uptick for the second quarter of recovery. Table 14 presents the correlation between adjusted productivity and the demand side indicator. As can be seen, the point estimate of correlation is substantially higher during turning points.

Table 13 - Consumer confidence changes around recessions

Period	Average group	Average rest	p-value	different s.d.
Recession	-6.35	0.16	0.01**	yes
Recession F1	1.07	-0.12	ns	yes
Recovery	5.33	-0.29	0.00***	no
Recovery F1	3.62	-0.22	0.02**	no
Recovery F2	-1.60	-0.02	ns	no
Recovery F3	1.55	-0.14	ns	no

Level quarterly changes of the University of Michigan Consumer Sentiment Index

Table 14 - Correlation productivity demand indicator by subsample

Correlation (di,dA)	Subsample	Estimate	Lower B. (90%)	Upper B. (90%)
ATFP	Whole Sample	20.3%	9.3%	30.8%
	Turning points	69.5%	38.1%	86.5%
	Rest Sample	12.9%	1.2%	24.1%
ACTFP	Whole Sample	32.2%	21.7%	41.9%
	Turning points	80.5%	57.5%	91.7%
	Rest Sample	21.6%	10.2%	32.4%

Demand indicator (di): Level quarterly changes of the University of Michigan Consumer Sentiment Index

[62]To match the appropriate frequency the variable used is the quarterly average of the three months composing the quarter.

3.6 Conclusion

The role of technology shocks in the business cycle is still an actively debated subject in macroeconomics. In general SVAR models tend to allocate only a small role to technology shocks at business cycle frequencies, whereas other types of models give them a larger role. The crucial assumption behind the SVAR models is to identify technology shocks as those having permanent effects. A new database of utilization adjusted productivity produced by Fernald (2012), presents, in principle, the opportunity to identify technology shocks other than through established long-run restrictions. Using this new database Sims (2011) finds that technology shocks can explain up to 60% of the cyclical variations in output.

In order to better understand to what extent the short run adjusted productivity movements identified by Sims can really be considered productivity shocks, I analyze in detail the business cycle properties of the Fernald database. Using the new database I uncover procyclical spikes of adjusted productivity during precisely the turning points of recessions, the 1st quarter of recessions and the 1st quarter of recoveries. Furthermore, the spikes are not observed in the remaining quarters of recessions and recoveries and account for the bulk of the output-adjusted productivity correlation at the quarterly frequency, leaving the rest of the sample with a very low correlation.

I show that the pro-cyclical spikes are neither a consequence of co-movements of related variables, nor due to turning points being exceptional periods in any other sense than their definition and the behavior of adjusted productivity. Furthermore, periods similar to turning points in terms of adjusted TFP behavior are very scarce within the US post-war sample. In consequence, I examine other possible causes, starting with technology shocks. Simulations in standard DSGE models illustrate the difficulty in replicating the observed output and technology patterns. As a competing hypothesis I examine whether demand can account for the reported empirical patterns. Pending further research, this seems to be a reasonable, albeit tentative, conclusion. SVAR identified demand shocks are crucial for explaining the stylized facts. Importantly, steps are taken to ensure that the estimated demand shocks cannot be plausibly interpreted as technology shocks. Furthermore, two plausible demand indicators present both: procyclical spikes during turning points and a differential correlation with adjusted productivity during these periods.

The potential implications of the procyclical spikes of adjusted productivity for the understanding of the business cycle are considerable, given the particular quarters when the productivity movements occur (during turning points). If they are caused by technology shocks, they could be the cause of recessions and recoveries and thus of much of the output variation at business cycle frequencies. By contrast, if they are not caused by technology shocks and are associated with demand movements - as I tentatively conclude - several consequences of interest arise. First, even when using utilization adjusted TFP, identifying technology shocks through short run SVAR restrictions is not justified, and can lead to overstating the role of technology in the business cycle. Second, the correlation between output and adjusted TFP at the quarterly frequency is substantially diminished. Third, changes in demand, whether exogenous or in response to other non-technology shocks, seem to play a role at both the start and end of recessions.

3.7 Appendix

Table A1a - ATFP growth around recessions

Period	Average group	Average rest	p-value	different sd
Recession L3	1.15	1.31	ns	yes
Recession L2	1.15	1.31	ns	no
Recession L1	2.50	1.26	ns	no
Recession	-0.26	1.37	0.057*	no
Recession F1	1.51	1.30	ns	no
Recovery	3.19	1.23	0.028**	no
Recovery F1	0.62	1.34	ns	yes
Recovery F2	1.01	1.41	0.009***	no
Recovery F3	1.36	1.13	ns	no

t tests of averages across group. Null hypothesis no difference.

Table A1b - ACTFP growth around recessions

Period	Average group	Average rest	p-value	different sd
Recession L3	0.40	0.92	ns	yes
Recession L2	0.79	0.90	ns	no
Recession L1	1.52	0.87	ns	no
Recession	-1.73	1.01	0.031**	no
Recession F1	0.10	0.93	ns	no
Recovery	4.78	0.73	0.000***	no
Recovery F1	1.20	0.88	ns	yes
Recovery F2	0.53	0.95	0.073*	no
Recovery F3	1.74	0.86	ns	no

t tests of averages across group. Null hypothesis no difference.

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