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Abstract

Are firms' expectations systematically too optimistic or too pessimistic? Does it matter? We use micro data from the West German manufacturing subset of the IFO Business Climate Survey to infer quarterly production changes at the firm level and combine them with production expectations over a quarterly horizon in the same survey to construct series of quantitative firm-specific expectation errors. We find that depending on the details of the empirical strategy at least 6 percent and at most 34 percent of firms systematically over- or underpredict their one-quarter-ahead upcoming production. In a simple neoclassical heterogeneous-firm model these expectational biases lead to factor misallocations that cause welfare losses which in the worst case are comparable to conventional estimates of the welfare costs of business cycles fluctuations. In more conservative calibrations the welfare losses are even smaller.

JEL-Code: D220, D840, E200, E220.

Keywords: survey data, expectation errors, expectation biases, optimism, pessimism, firm data, heterogeneous firms.

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1 Introduction

Are firms' expectations systematically too optimistic or too pessimistic? Firms, based on expectations about their future business situation, decide about the allocation of an economy's capital stock and labor supply. If firms' expectations are biased, an economy's factor allocation is likely to be suboptimal compared to an economy populated by firms with unbiased expectations. How large are the welfare losses from the resulting factor misallocations? This paper, using business survey data from Germany, provides quantitative answers to these questions. We find that at most a third of firms in the sample systematically over- or underpredict their one-quarter-ahead upcoming production; these expectational biases lead to welfare losses that are typically not larger than conventional estimates of the welfare costs of business cycles fluctuations.

Little is known empirically about firms' expectation formation.[1] There is an accounting literature (e.g. McDonald, 1973, Firth and Smith, 1992, Brown et al., 2000), which finds that managers tend to bias their public earnings and dividend forecasts upward, presumably for strategic reasons to attract investors. Malmedier and Tate (2005, 2008) using data on risk exposure in firms' investment strategies to measure CEO overconfidence, investigate the relationship between CEO overconfidence and corporate investment. These literatures rely on either publicly announced expectations or ex-post behavior to measure firms' expectations. Business survey data on expectations and realizations are less likely to suffer from strategic forecasting behavior, as they are highly confidential micro data and can only be accessed under strict non-disclosure agreements, if at all. These survey data have been used in the literature to study rationality and unbiasedness of firms' expectations: Anderson et al. (1954) conduct a very early study on qualitative expectation errors using the first few installments of the IFO Business Climate Survey. Nerlove (1983) uses German (from IFO) and French data on firms' expectations about idiosyncratic firm variables (such as prices, demand, etc.). Tompkinson and Common (1983) study expectations about idiosyncratic firm variables in the U.K. manufacturing sector and Zimmermann and Kawasaki (1986), using IFO price expectation and realization data, test whether firms are rational about the development of the market prices of their own commodities. All these studies have in common

[1] Expectation formation of households is somewhat better understood: for instance, Souleles (2004), using data from the Michigan Survey of Consumers, and Bovi (2009), using the harmonized European consumer surveys, present evidence that household expectations are not rational. Agents systematically assess their current situation overcritically and form their expectations overoptimistically. On the theory side, Brunnermeier and Parker (2005) present a model where agents optimally bias their expectations about the future upwards to increase their expected life time utility. Jaimovich and Rebelo (2007) study a business cycle model with overoptimism with respect to the realization of investment-specific shocks, without, however, using micro data for calibration. Hassan and Mertens (2011) argue that small expectation errors of stock market investors can have first order effects on welfare.

that they usually find some degree of deviation from rationality. Nonetheless as e.g. Pesaran and Wheale (2006) state the analysis of individual response data of business survey data is underdeveloped.

Progress in the empirical literature on firms' expectation formation has been slow because of formidable data requirements. Ideally, researchers need high-frequency quantitative expectation and realization data on firm-specific variables for a large (and representative) cross-sections of firms, such as: "By how much do you expect your production to grow over the next quarter? By how much did your production grow during the preceding quarter?" These data need to be available over long time horizons to construct firm histories of expectation errors and to ensure that specific cyclical episodes do not bias results; after all, in booms we should expect to see upward expectation errors, and vice versa in recessions.

However, high frequency business survey data about idiosyncratic expectations and realizations are usually qualitative,[2] indeed trichotomous, in nature: "We expect our production to increase, decrease, stay the same over the next three months". While useful, qualitative information has its limits, in particular when forecasting errors need to be aggregated over time in order to measure the long-run average forecasting errors of firms and possible biases therein. How does one aggregate a qualitative forecasting error of $+1$ (up) today and -1 (down) tomorrow?[3] Therefore, Müller (2011) uses quantitative expectations about plants' sales and employment development over a year from the annual IAB Establishment Panel in Germany to measure whether firms are overoptimistic or overpessimistic. He finds strong evidence for the existence of both types of firms. However, the IAB Establishment Panel is still rather short (starting in 1993) and of low frequency.

In our analysis we use firm-level micro data from the IFO Business Climate Survey (IFO-BCS) that allow us to construct quantitative expectation errors for firms' production. We note that we do not observe directly in the IFO-BCS the aforementioned quantitative questions "By how much do you expect your production to grow over the next quarter? By how much did your production grow during the preceding quarter?". But we can combine answers to other qualitative and quantitative questions that under certain assumptions allow us the construction of quantitative expectation errors for firms' production. While not ideal, we view this as an attempt to use the best available data and inform quantitative assessments of the welfare impact of expectational biases.

[2] De Leeuw and McKelvey (1981) study quantitative annual expectation data about aggregate prices from a BEA survey of business expenditures on plant and equipment in the U.S. and find that firms do not have rational expectations.

[3] This is a problem, even when qualitative expectation data predict quantitative ex-post data rather well, which is what Lui et al. (2008) find, using survey data from the 'Confederacy of British Industry' business survey and ex-post administrative data.

We also note that we cannot measure surprises with respect to truly exogenous driving forces, such as technology or demand shocks. However, to the best of our knowledge there is no business survey in the world which does or even would ask these questions directly. Nevertheless, surprises with respect to endogenous variables, such as production, can be informative about truly exogenous surprises when viewed through the lens of a structural model of the firm. We will make use of this insight in the second half of the paper.

The IFO-BCS is a monthly qualitative business survey that is supplemented on a quarterly basis with quantitative questions. Given appropriate assumptions, we can combine the qualitative three-month ahead production outlook from the monthly survey with the quantitative change in percentage capacity utilization from the quarterly supplement to compute idiosyncratic quarterly, one-quarter-ahead production expectation errors. We do this for the manufacturing part of the IFO-BCS from 1980 on and thus construct a panel of quarterly firm-level production expectation errors over thirty years.

Limiting our analysis to firms with at least eight years of observations we compute long-run averages of firms' expectation errors and analyze their distributions. To classify firms as optimists or pessimists, we test for each firm whether its average expectation error is significantly different from zero in statistical sense, at the 5 percent level. At least 6 percent and at most 34 percent of firms consistently over- or underpredict their one-quarter-ahead upcoming production. The optimist firms, for example, overpredict their production in the baseline specification by 3.5 percent on average.

To gauge the implications of these expectational biases we perform a simple welfare calculation, using a neoclassical heterogeneous-firm model where firms decide about their factor demands before they know their idiosyncratic productivity levels. We calibrate the fractions of optimistic and pessimistic firms and the extent of their expectational biases to the distributional properties of production expectation errors in the IFO-BCS. Overoptimistic firms hire too many workers and build up capital stocks that are too high. Overpessimistic firms do not demand enough inputs. We then compare the welfare in an economy which is populated by firms with a distribution of production expectation errors that approximates the one in the data to a world that is only populated by firms with zero long-run expectation errors. We robustly find that the welfare losses from expectational errors are small, at worst around 0.1 per cent in terms of consumption equivalents, more likely smaller than these conventional estimates of the welfare costs of business cycles.

The remainder of this paper is structured as follows. The next section describes the IFO-BCS and the construction of the idiosyncratic production expectation errors from it. Section 3 introduces the heterogeneous-firm model, our measurement device. Section 4 presents and discusses the welfare results. Section 5 provides a series of robustness checks.

Section 6 concludes. Details on the empirics and the computations are relegated to various appendices.

2 Evidence from the IFO Business Climate Survey

2.1 The IFO Business Climate Survey

The IFO Business Climate index is a much-followed leading indicator for economic activity in Germany. It is based on a firm survey, the IFO Business Climate Survey (IFO-BCS), which has been conducted since 1949. To the best of our knowledge it is the first business survey that started to ask manufacturing firms about their own output and price expectations (see Becker and Wohlrabe, 2008, for details).[4] Since then the survey design of the IFO Business Climate index was adopted by other surveys such as the Confederation of British Industry for the UK manufacturing sector or the Tankan survey for Japanese firms. Due to longitudinal consistency problems in other sectors and the availability of micro data in a processable form we limit our analysis to the manufacturing sector from 1980 until 2010. Again for reasons of longitudinal consistency, our analysis excludes East German firms.

One of the IFO-BCS's main advantages is the high number of survey participants. The average number of respondents at the beginning of our sample is approximately 5,000; towards the end it is about 2,000.[5] Participation in the survey is voluntary and confidential. Thus, there is little incentive for firms to provide overoptimistic forecasts as a signal to investors. There is some fraction of firms that are only one time participants. However, conditional on staying two months in the survey, most firms continue on and this allows us to construct an (unbalanced) panel data set of production expectation errors. For our narrow, very conservative definition of expectation errors the final baseline panel consists of 696 firms for which we have at least 32 quarterly observations each; for a broader definition of expectation errors the panel contains 3,679 firms, again with at least 32 quarterly observations.

2.2 Construction of Quantitative Production Expectation Errors

To construct firms' quantitative production expectation errors we would ideally need the following quantitative information about production expectations and realizations: "By how

[4] The first consumer survey asking for information on expectations was conducted by the United States' Department of Agriculture in 1944. The Livingston survey, the oldest survey of economists' expectations concerning macroeconomic variables, started in 1946.

[5] Strictly speaking, the IFO-BCS is a survey at the product level, so that these numbers do not exactly correspond to firms.

much do you expect your production to grow over the next quarter? By how much did your production grow in the preceding quarter?" To the best of our knowledge there is no firm survey that asks these questions for a long time horizon and repeatedly at underyearly frequencies. However, the quantitative quarterly supplement of the IFO survey allows us to construct - under certain assumptions - quantitative production expectations and quantitative production realizations. We are thus able to construct a panel of quantitative quarterly production expectation errors for the last thirty years. While not ideal, we view this paper as an attempt to use the best available data to address the question of how expectational biases impact welfare.

Specifically, we use the following supplementary question about capacity utilization to compute production changes:[6]

Q 1 *"Supplementary Question: The utilisation of our production equipment for producing XY (customary full utilization = 100) currently amounts to..%."*

30	40	50	60	70	75	80	85	90	95	100	more than 100 % namely

We start from the following production relationship of an individual firm i:

$$y_{i,t}^{act} = u_{i,t} y_{i,t}^{pot}, \tag{1}$$

where $y_{i,t}^{act}$ denotes the firm's actual output, $y_{i,t}^{pot}$ its potential output level and $u_{i,t}$ the level of capacity utilization. Only $u_{i,t}$ is directly observable in the IFO-BCS. Taking the natural logarithm and the three-month difference, we get:[7]

$$\Delta \log y_{i,t}^{act} = \Delta \log u_{i,t} + \Delta \log y_{i,t}^{pot}. \tag{2}$$

Under the assumption that potential output remains constant, $\Delta \log y_{i,t}^{pot} = 0$, percentage changes in actual output can be recovered from percentage changes in capacity utilization. To implement this idea we restrict the analysis to firms of which we can reasonably expect that they did not change their production capacity in the preceding quarter, making use of the following two questions in the IFO-BCS:

[6]Here we provide a translation, for the German original see Appendix A.

[7]Time intervals are months. For us to construct an expectation error in t, we need an observation for capacity utilization in t and $t-3$.

Q 2 *"Expectations for the next three months: Employment related to the production of XY in domestic production unit(s) will probably increase, roughly stay the same, decrease."*

Q 3 *"Supplementary Question: We evaluate our technical production capacity with reference to the backlog of orders on books and to orders expected in the next twelve months as more than sufficient, sufficient, insufficient."*

Given hiring frictions in the labor market, we view a firm's expectation, stated in $t-3$, that its employment level will remain the same in the next three months as highly indicative that its productive capacity did not change between $t-3$ and t. Similarly, given capital adjustment frictions, we view a firm's statement, again in $t-3$, that its technical production capacity is sufficient for the future incoming orders as suggestive that this firm has no reason to change its production capacity in the near future. To be conservative we require a firm to satisfy both criteria in $t-3$ for us to assume that its production capacity has not changed between $t-3$ and t. In this case, we use the quarterly percentage change in capacity utilization in t as a proxy for the quarterly percentage change in production in t. The existence of non-convex or kinked adjustment costs for capital and labor adjustment as well as time to build (see Davis and Haltiwanger, 1992, as well as Doms and Dunne, 1998) make this a reasonable assumption.

To derive production expectation errors we also need information on firms' production expectations. This allows us to compute production *surprises* out of mere production *changes*. In the IFO-BCS firms report only qualitative production expectations:

Q 4 *"Expectations for the next three months: Our domestic production activities with respect to product XY will (without taking into account differences in the length of months or seasonal fluctuations) increase, roughly stay the same, decrease."*

Qualitative expectations have a built-in asymmetry in the sense that the middle category also constitutes a quantitative expectation, zero or close-to-zero change, whereas the increase and decrease categories convey no quantitative information. We therefore proceed in two steps. First, we consider only firms whose answer to Q4 is that their production level, $y_{i,t}^{act}$, will not change in the next three months. Under the assumption that $y_{i,t}^{pot}$ remains constant over this time period, all $\Delta \log u_{i,t}$ are automatically expectation errors. In a second step we extend our analysis to arbitrary qualitative production expectations. This will give us a broader picture of expectation errors, albeit with the added cost of more necessary assumptions.

We also clean our sample from firm-quarter observations with extreme capacity utilization outliers, i.e. those that exceed 150%, and from firm-quarter observations with inconsistent statements. To determine the latter we consider the following monthly qualitative IFO-BCS question concerning actual production changes in the months t, $t-1$, $t-2$:

Q 5 *"Trends in the last month: Our domestic production activities with respect to product XY have (without taking into account differences in the length of months or seasonal fluctuations) increased, roughly stayed the same, decreased."*

We drop all observations as inconsistent in which firms report a strictly positive (negative) change in $\Delta \log u_{i,t}$ and no positive (negative) change in Q5 in the last 3 months. For firms that report $\Delta \log u_{i,t} = 0$, we proceed as follows: Unless firms in Q5 either answer three times in a row that production did not change, or unless they have at least one "Increase" *and* one "Decrease" in their three answers, we drop them as inconsistent.

In our starting sample we have 381,854 firm-level observations for $u_{i,t}$, i.e. 381,854 firm-quarter observations. The number of outliers is quite small and corresponds to 238 firm-quarter observations. We are able to compute 343,023 changes in capacity utilization, $\Delta \log u_{i,t}$. For 177,432 observations we can assume that their $y_{i,t}^{pot}$ has not changed during the last three months, due to Q2 and Q3. We classify 69,669 observations as inconsistent and drop them for the baseline. Our final baseline sample consists of 107,763 observations for $y_{i,t}^{act}$.

2.2.1 Quantitative Expectation Errors under Constant Qualitative Production Expectations

If the production capacity can be assumed not to have changed in the preceding quarter, and if no change in production was expected three months prior, a change in capacity utilization, $\Delta \log u_{i,t}$, is also a production expectation error of firm i in month t. Notice that the signing convention for a production expectation error is such that we subtract the expectation from the actual change. We first restrict our analysis to the subset of firm-quarter observations that satisfy these assumptions. For this case, Figure 1 illustrates the move from capacity utilization changes to production expectation errors.

Figure 1: Link between Capacity Utilization and Production Expectation Errors

Prerequisite: Firm i passes the outlier and inconsistency test (Q1 and Q5)

Firm i has an observation for a change in capacity utilization $\Delta \log u_{i,t}$ (Q1)

No change in potential output $\Delta \log y_{i,t}^{pot}$

Firm i answers "Constant employment expectations" (Q2)

and "Technical production capacity is sufficient" (Q3) in $t-3$

$\Delta \log u_{i,t}$ is a production change $\Delta \log y_{i,t}^{act}$

No expected production change

Qualitative production expectations in $t-3$ are constant (Q4)

$\Delta \log u_{i,t}$ is a quantitative production expectation error

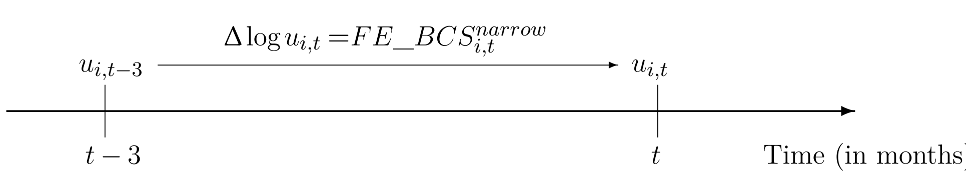
Notes: The time dimension t is measured in months.

Figure 2 illustrates the exact timing of the questions in the IFO-BCS that we use to compute production expectation errors. As a first pass we consider only firms which state in period $t-3$ that their production level, employment level and technical production capacity will remain the same in the next three months. Then we compute $\Delta \log u_{i,t}$ three months later in t. These $\Delta \log u_{i,t}$ constitute our narrow definition of production expectation errors. We denote them by $FE\_BCS_{i,t}^{narrow}$.

Figure 2: Derivation of Production Expectation Errors under Constant Production Expectations - Timing

Prerequisite: Firm i passes the outlier and inconsistency test (Q1 and Q5)

Firm i states in period $t-3$:
Constant employment expectations (Q2)
Sufficient technical capacity (Q3)
Constant production expectations (Q4)



2.2.2 Quantitative Expectation Errors under General Production Expectations

The derivation of quantitative production expectation errors for firms with increasing or decreasing qualitative production expectations in Q4 requires additional assumptions. We admit at the outset that these assumptions may not be too palatable. However, we view this as an attempt to measure firms' quantitative production expectation errors as best as we can, *given the limited data available*. We take the following four steps. First, we define a qualitative index of production changes. Specifically, we compute a firm-specific activity variable, $REALIZ_{i,t}$, as the sum of the increase-instances minus the sum of the decrease-instances in question Q5 over the last three months going backward from t. In a second step, we use these qualitative production changes to determine qualitative expectation errors with question Q4.[8] Then, using the conditions about employment expectations and adequacy of technical capacity, we map qualitative production changes into quantitative production changes. In a final step, we convert these quantitative production changes into quantitative production expectation errors for all firms that pass the aforementioned outlier and inconsistency tests.

The basic idea is to assign firms with large *qualitative* production expectation errors – for example a firm expecting its production to go up over the next three months, but then reporting only production declines – large *quantitative* production expectation errors, derived from a mapping between qualitative and quantitative production changes. The expectation errors for firms with constant production expectations remain the same as in the previous section. We denote this measure of quantitative production expectation errors under general production expectations by $FE\_BCS_{i,t}^{broad}$. Details of the construction can be found in Appendix B.

2.3 Results

We next compute the average firm-specific production expectation error over all time periods for which we have data. We restrict our sample to firms that have at least 32 observations or eight years of expectation errors, for both $FE\_BCS_{i,t}^{narrow}$ and $FE\_BCS_{i,t}^{broad}$. The average firm-specific expectation errors are denoted by $AFE\_BCS_{i}^{narrow}$ and $AFE\_BCS_{i}^{broad}$.

Table 1 displays the distributions of firms' average expectation errors.[9] Note that posi-

[8]This procedure follows Bachmann, Elstner, and Sims (2013).

[9]We show in Figure 6 of Appendix C the corresponding histograms of these distributions. Tables 11 and 12 in Appendix D show the analogue of Table 1, when we, respectively, include firm-quarter observations for firms that have an "inconsistent" production change statement for that quarter, and when we use 16 quarterly expectation error observations (or four years) instead of 32 as the cut-off criterion to compute the $AFE\_BCS_{i}^{narrow}$ or $AFE\_BCS_{i}^{broad}$.

Table 1: Firm-Specific Average Production Expectation Errors (IFO-BCS)

Statistics	$AFE\_BCS_i^{narrow}$	$AFE\_BCS_i^{broad}$
Obs	696	3,679
Mean	-0.0064	-0.0255
Std.Dev.	0.0162	0.0302
Percentiles		
5th	-0.0339	-0.0822
10th	-0.0240	-0.0645
25th	-0.0118	-0.0401
50th	-0.0030	-0.0205
75th	0.0014	-0.0059
90th	0.0068	0.0058
95th	0.0120	0.0134
# Optimists	38 (5.5%)	1,213 (33.0%)
# Pessimists	6 (0.9%)	48 (1.3%)
# Realists	652 (93.7%)	2,418 (65.7%)

Notes: This table provides a summary of the distributions of $AFE\_BCS_i^{narrow}$ and $AFE\_BCS_i^{broad}$. In the last three rows we report the number of firms which are classified as optimists, pessimists and realists, respectively. We define optimistic firms as those firms which feature a negative average expectation error that is significantly different from zero, at the five percent level. Pessimistic firms are defined as those firms with a positive average expectation error that is significantly different from zero, at the five percent level.

tive values of $AFE\_BCS_i^{narrow}$ or $AFE\_BCS_i^{broad}$ indicate that a firm was on average too pessimistic in the sense that its predicted production changes were on average lower than its actual production changes. Especially for $AFE\_BCS_i^{broad}$ the distribution is skewed towards negative values and at least 25 percent of all firms have long run averages of expectation errors which are too optimistic by 4 percent or more.[10] These numbers alone, however, are not sufficient to assess whether a firm has biased expectations. To provide evidence for expectational biases we need to consider the second moment of firm-specific shocks as well. Firms operate in different economic environments and face different sizes of shocks. Therefore, analyzing only average expectation errors can be misleading.

The panel structure of the IFO-BCS allows us to address this issue. We test for each firm whether its average expectation error is statistically significantly different from zero. Adapting the procedure in Souleles (2004), we regress for each firm all its observations of $FE\_BCS_{i,t}^{narrow}$ and $FE\_BCS_{i,t}^{broad}$ on a constant. Then we use two-sided t-tests with a 5 percent significance level in order to assess whether the individual firm-specific average expectation error is significantly different from zero. We define optimistic firms as those

[10]Excluding the periods 1990 to 1992 (German reunification) and 2008 to 2009 (recession after the collapse of Lehman) does not change noticeably our results shown in Table 1.

firms which feature a negative average expectation error that is significantly different from zero. Pessimistic firms are defined as those firms with a positive average expectation error that is significantly different from zero.

We find for $AFE\_BCS_i^{narrow}$ and $AFE\_BCS_i^{broad}$ that at least 20 percent of firms have average expectation errors that deviate one standard deviation of the corresponding distribution or more from zero. However, in the case of $AFE\_BCS_i^{narrow}$ this difference from zero is only significant for 6 percent of all considered firms. For $AFE\_BCS_i^{broad}$ we end up classifying more than 30 percent of firms as optimists. For both definitions of forecast errors we see that the distribution of average forecast errors is skewed towards overoptimism. The optimist firms overpredict their production by 3.5 percent (5.6 percent for the broad definition) on average, which corresponds to 2.2 times (1.8 times) the standard deviation of the distribution of firms' production expectation errors. The pessimist firms underpredict their production by 2.4 percent (3.3 percent for the broad definition) on average, which corresponds to 1.5 times (1.1 times) the standard deviation of the distribution of firms' production expectation errors.

It is instructive to analyze whether the existence of expectational biases covaries with observable firm-specific characteristics. To do so, we compute contingency tables. Specifically, we check whether firm-specific characteristics like exporter status or firm size, determined by the average number of employees over the sample, induce a higher probability to observe a "realist" or a "nonrealist" firm. A summary of the results is shown in Table 2. To test whether statistical relationships are significant we use Pearson's χ^2-test. The null hypothesis of this test states that both firm-specific characteristics are independent of each other, i.e. under the null hypothesis the distribution of expectational biases is independent of firm size or exporter status. Our results show, however, that, in particular in the case of $AFE\_BCS_i^{broad}$, systematic relationships between firm size and expectational biases exist. While smaller firms are more likely to be too optimistic in their expectations, larger firms seem to be more "realistic". For $AFE\_BCS_i^{broad}$, we observe that 38.9 percent of all firms with less than 50 employees are overoptimistic firms, whereas only 24.6 percent of firms with more than 1000 employees are optimists. This result reflects the idea that larger firms are likely to put more resources into analyzing their current and upcoming business environment than smaller firms. Regarding the exporter status we find that exporting firms tend to be more "realistic" firms.[11]

[11] To determine exporter status we use the monthly IFO-BCS question concerning expected export trade. If a firm stated in more than half its answers that it does not export, that firm is classified as non-exporter.

Table 2: Relationship of Firms' Expectational Biases with Firms' Characteristics

Characteristics	# Observations	# Realists	# Optimists	# Pessimists
Quantitative Expectation Errors under Constant Production Expectations: $AFE\_BCS_i^{narrow}$				
All Firms	696 (100.0%)	652 (93.7%)	38 (5.5%)	6 (0.9%)
Exporter	593 (100.0%)	558 (94.1%)	30 (5.1%)	5 (0.8%)
Firm Size				
less than 50 employees	103 (100.0%)	92 (89.3%)**	11 (10.7%)**	0 (0.0%)
$50 - 199$ employees	267 (100.0%)	251 (94.0%)	12 (4.5%)	4 (1.5%)
$200 - 499$ employees	166 (100.0%)	156 (94.0%)	9 (5.4%)	1 (0.6%)
$500 - 999$ employees	91 (100.0%)	87 (95.6%)	3 (3.3%)	1 (1.1%)
more than $1,000$ employees	69 (100.0%)	66 (95.7%)	3 (4.4%)	0 (0.0%)
Quantitative Expectation Errors under General Production Expectations: $AFE\_BCS_i^{broad}$				
All Firms	3,679 (100.0%)	2,418 (65.7%)	1,213 (33.0%)	48 (1.3%)
Exporter	2,890 (100.0%)	1,926 (66.6%)**	930 (32.2%)*	34 (1.2%)
Firm Size				
less than 50 employees	803 (100.0%)	482 (59.9%)***	311 (38.9%)***	10 (1.3%)
$50 - 199$ employees	1,399 (100.0%)	903 (64.6%)	480 (34.4%)	16 (1.1%)
$200 - 499$ employees	803 (100.0%)	547 (68.1%)	248 (30.9%)	8 (1.0%)
$500 - 999$ employees	345 (100.0%)	249 (72.2%)***	93 (27.0%)**	3 (0.9%)
more than $1,000$ employees	329 (100.0%)	237 (72.0%)**	81 (24.6%)***	11 (3.3%)***

Notes: This table provides the numbers of firms that feature specific observable firm-level characteristics and expectational biases. The numbers in parentheses are proportions. To check for independence between those firm level characteristics we use Pearson's χ^2-test . ***: $p<0.01$; **: $p<0.05$; *: $p<0.1$.

3 A Model

3.1 Firms

The model economy is populated by a unit mass continuum of ex ante identical, but ex post potentially heterogeneous firms. They produce a final generic good using a diminishing returns to scale production function with capital and labor as inputs. In addition, production is affected by idiosyncratic productivity shocks. Specifically, an individual firm i's production function is given by:

$$y_{i,t} = z_{i,t} k_{i,t}^{\theta} n_{i,t}^{\nu}, \tag{3}$$

where $z_{i,t}$ denotes the idiosyncratic productivity level, and $k_{i,t}$ and $n_{i,t}$ denote the firm-specific capital stock and employment level, respectively. We assume competitive factor markets. Firms pay a real wage w_t for one unit of labor input and a rental rate r_t for one unit of capital input.

To incorporate expectational biases, we assume that firms decide about their factor demands in period t before knowing their productivity levels $z_{i,t}$. Instead, firms form expectations about $z_{i,t}$ on the basis of $z_{i,t-1}$. We further assume that the natural logarithm of $z_{i,t}$ follows a three-state Markov chain on the states $[\epsilon, 0, -\epsilon]$ with the following symmetric transition matrix P^{obj} (in a robustness check we will consider also an asymmetric specification):

$$P^{obj} = \begin{pmatrix} \rho_1 & \rho_2 & 1-\rho_1-\rho_2 \\ \rho_3 & 1-2\rho_3 & \rho_3 \\ 1-\rho_1-\rho_2 & \rho_2 & \rho_1 \end{pmatrix}, \tag{4}$$

where $\rho_1 + \rho_2 < 1$ and $\rho_3 < 0.5$. P^{obj} is the actual transition matrix of the idiosyncratic productivity process. Rational firms would use this transition matrix to compute expectations about their idiosyncratic productivity levels. Some firms, however, which we call optimists and pessimists form their expectations with different transition matrices, $P^{subj,opt}$ and $P^{subj,pess}$. Relative to P^{obj}, $P^{subj,opt}$ and $P^{subj,pess}$ feature expectational biases which we model parsimoniously with a parameter ϕ. This parameter is introduced additively into the true transition matrix P^{obj}. Specifically, the subjective transition matrix of an optimist looks as follows:

$$P^{subj,opt} = \begin{pmatrix} \rho_1 & \rho_2 & 1-\rho_1-\rho_2 \\ \rho_3+\phi & 1-2\rho_3 & \rho_3-\phi \\ 1-\rho_1-\rho_2+\phi & \rho_2+\phi & \rho_1-2\phi \end{pmatrix}. \tag{5}$$

The subjective transition matrix for a pessimist is just analogous:

$$P^{subj,pess} = \begin{pmatrix} \rho_1 - 2\phi & \rho_2 + \phi & 1 - \rho_1 - \rho_2 + \phi \\ \rho_3 - \phi & 1 - 2\rho_3 & \rho_3 + \phi \\ 1 - \rho_1 - \rho_2 & \rho_2 & \rho_1 \end{pmatrix}. \tag{6}$$

With this expectation formation process the optimal factor demands are given by:

$$n_{i,t} = \left[\left(\frac{\nu E[z_{i,t}|z_{i,t-1}]}{w_t} \right) \left(\frac{\theta w_t}{\nu r_t} \right)^{\theta} \right]^{\frac{1}{1-\theta-\nu}} \tag{7}$$

$$k_{i,t} = \frac{\theta w_t}{\nu r_t} n_{i,t}. \tag{8}$$

Note that if a firm expects a higher expected value of its productivity level $E[z_{i,t}|z_{i,t-1}]$, it will demand more capital and labor. This implies that overoptimistic firms hire too many workers and build up capital stocks that are too high. In the other direction overpessimistic firms do not demand enough inputs. This leads to factor misallocation and, potentially, to welfare losses.

3.2 Households

We assume a representative household with time separable preferences who maximizes the following instantaneous utility function:

$$U_t = \log C_t - \frac{A}{1+\eta} {N_t}^{1+\eta}, \tag{9}$$

where C_t is aggregate consumption and N_t denotes aggregate employment. η is the inverse of the Frisch elasticity of labor supply. The budget constraint of the household is given by:

$$w_t N_t + (1 - \delta + r_t) K_t + \Pi_t = K_{t+1} + C_t, \tag{10}$$

where δ is the depreciation rate, K_t the aggregate capital stock and Π_t denotes aggregate profits. We assume that all firms are owned by the representative household who does not know the types of the firms, for instance whether they are realists, optimists or pessimists. After solving the intertemporal optimization problem of the household we get the usual first-order conditions:

$$w_t = A C_t N_t^{\eta}, \tag{11}$$

$$\frac{1}{C_t} = \beta E_t \left[\frac{1 + r_{t+1} - \delta}{C_{t+1}} \right]. \tag{12}$$

3.3 Equilibrium

Given an initial capital stock, K_0, and a sequence of shocks $\{\{z_{i,t}\}_{i=0}^{\infty}\}_{t=0}^{\infty}$ an equilibrium of this economy is defined as a time path of quantities $\{\{y_{i,t}\}_{i=0}^{\infty}, \{k_{i,t}\}_{i=0}^{\infty}, \{n_{i,t}\}_{i=0}^{\infty}, C_t, K_t, N_t\}_{t=0}^{\infty}$ and a time path of prices $\{w_t, r_t\}_{t=0}^{\infty}$ that satisfy:

1. *Firm optimality:* Taking $\{w_t, r_t\}_{t=0}^{\infty}$ as given, the optimal factor demands for $n_{i,t}$ and $k_{i,t}$ are determined according to equations (7) and (8).

2. *Household optimality:* Taking $\{w_t, r_t\}_{t=0}^{\infty}$ and K_0 as given, the household's consumption and labor supply satisfy (10), (11) and (12).

3. *Commodity market clearing:*

$$C_t = \int z_{i,t} k_{i,t}^{\theta} n_{i,t}^{\nu} \, di - \left(K_{t+1} - (1 - \delta) \int k_{i,t} \, di \right)$$

4. *Labor market clearing:*

$$N_t = \int n_{i,t} \, di$$

3.4 Calibration

The model period is a quarter. Table 3 gives an overview of the standard parameter choices for calibration: Bachmann and Bayer (2011) compute from national accounting data an average annual depreciation rate of 0.094 for Germany. They also estimate the median factor shares of labor and capital in the German manufacturing sector from firm-level micro data: $\theta = 0.2075$ and $\nu = 0.5565$. The discount factor generates an annual real interest rate of 2 percent. We fix the Frisch elasticity of labor supply at unity. The disutility parameter of labor, A, is chosen to ensure that the average time spent at work by the representative household is 0.33.

Table 3: Standard Parameter Values

Baseline Calibration		
Parameter	Description	Value
δ	Depreciation rate	0.0235
θ	Decreasing returns to capital	0.2075
ν	Decreasing returns to labor	0.5565
β	Discount factor	0.9950
η	Inverse elasticity of labor supply	1.0000
A	Disutility of labor	6.0000

The remaining parameters ρ_1, ρ_2, ρ_3, ϕ and ϵ are calibrated using the IFO-BCS. As a reminder, P^{obj}, the true transition matrix for the idiosyncratic productivity shock process, is given by:

$$P^{obj} = \begin{pmatrix} \rho_1 & \rho_2 & 1-\rho_1-\rho_2 \\ \rho_3 & 1-2\rho_3 & \rho_3 \\ 1-\rho_1-\rho_2 & \rho_2 & \rho_1 \end{pmatrix}.$$

Note that ρ_1, ρ_2 and ρ_3 define transition probabilities conditional on a certain economic state. The IFO-BCS provides such information in a qualitative way with the following question concerning the current business situation:

Q 6 *"Current Situation: We evaluate our business situation with respect to product XY as good, satisfactory, unsatisfactory."*

We start with the calibration of ρ_3. These entries define situations in which the economic states of the firms do not change. Suppose that a firm is in the intermediate economic state. This state will not change with probability $(1-2\rho_3)$. Therefore, we compute for each quarter the fraction of firms with no upcoming production change, i.e. $REALIZ_{i,t+3}$ is equal to zero, conditional on a normal current business situation.[12] The time series average of these fractions provides an estimate of $(1-2\rho_3)$.[13]

The probability for firms to remain in either the good or bad economic state is given by ρ_1. We compute the fractions of firms that have no decrease in their production level over the next three months, i.e. $REALIZ_{i,t+3}$ is greater or equal to zero, conditional on a good

[12] $REALIZ_{i,t}$ is defined as the sum of the Increase-instances minus the sum of the Decrease-instances in question Q5 over the last three months going backward from t. $REALIZ_{i,t}$ can have seven possible values that live in the interval [-3,3].

[13] As before we use only those firms that pass the outlier and consistency test (Q1 and Q5).

current business situation. Similarly, we compute the fraction of firms that have no increase in their production level over the next three months, i.e. $REALIZ_{i,t+3}$ is less or equal to zero, conditional on a bad current business situation. Finally, we take the average of the two time-series averages to get ρ_1.

To calibrate ρ_2 we compute the unconditional quarterly fractions of firms which change their production level over the upcoming quarter, i.e. $REALIZ_{i,t+3}$ is unequal to zero. The time-series average of these fractions provides an empirical moment that has to be matched by the model. Given ρ_1 and ρ_3 we find a value for ρ_2 that yields the same fraction of firms changing their economic state in the model. The first three rows of Table 4 summarize the calibration results so far.

Table 4: Parameter Values of P^{obj}, ϕ, ϵ

Baseline Calibration			
Parameter	Description	$FE_{i,t}^{narrow}$	$FE_{i,t}^{broad}$
ρ_1	Parameter Transition Matrix	0.8622	0.8488
ρ_2	Parameter Transition Matrix	0.1378	0.1512
ρ_3	Parameter Transition Matrix	0.2073	0.2660
ϵ	Parameter of Technology State	0.0959	0.1914
ϕ	Expectational Bias Parameter	0.1486	0.1068

The calibration of ϵ and ϕ requires the simulation of the entire model and has to be done jointly. In a first step we compute separately for the "realist" and "nonrealist" firms the individual averages of the absolute value of their expectation errors. The average absolute expectation error for "realist" firms identifies ϵ, the same statistic for "nonrealists" identifies ϕ. For a given choice of the forecast error type in the data, each guess for ϵ and ϕ allows us to compute the model average absolute forecast errors for "realist" and "nonrealist" firms. We pick ϵ and ϕ such that the model numbers correspond to their data counterparts. The calibrated values of ϕ and ϵ are shown in the last two rows of Table 4.

To gauge how these Markov chains behave in terms of standard AR(1) modelling we simulate 100 times the Markov chain defined by P^{obj} and ϵ with 20,000 time series observations each. Then we estimate AR(1)-regressions on each of these time series. Table 5 displays the average of the 100 AR(1)-coefficients and standard errors of the regressions.

Table 5: AR(1)-Properties of the Calibrated Idiosyncratic Shock Processes

	AR(1)-coefficient	Standard Error of Regression
$FE_{i,t}^{narrow}$	0.8619	0.0421
$FE_{i,t}^{broad}$	0.8485	0.0893

Notes: This table shows in the first column the average of the estimated 100 AR(1)-coefficients for the simulated Markov chains explained in the text for $FE_{i,t}^{narrow}$ and $FE_{i,t}^{broad}$. The second column displays the average of the standard errors of these regressions. Each Markov chain has been simulated over 20,000 observations.

4 Welfare Calculations

To gauge the economic significance of the observed expectational biases in the IFO-BCS, we compare the lifetime utility of the representative agent in the steady state of the actual economy with biased expectations, denoted by $Welfare^{act}$, with her lifetime utility in the following hypothetical scenario: suppose at some point in time t_0 all optimist and pessimist firms become "realists" and use P^{obj} to form their expectations. Welfare is determined by the discounted utility function of the representative household:

$$Welfare = \sum_{t=0}^{\infty} \beta^t \left(\log C_t - \frac{A}{1+\eta} N_t^{1+\eta} \right). \tag{13}$$

At t_0 this economy starts out at the steady state capital stock of the economy with expectational biases and then transitions towards a new steady state. We can compute the welfare of the representative household along this transition path, denoted by $Welfare^{hypo}$, according to equation (13). Then we determine the welfare loss as the percent difference of $Welfare^{act}$ and $Welfare^{hypo}$. We also compute the consumption equivalent (in percent of the steady state consumption of the actual economy with expectational biases). Formally, we find a $\overline{C}$, such that:

$$\sum_{t=0}^{\infty} \beta^t \left(\log(C_t^{act} + \overline{C}) - \frac{A}{1+\eta} \left(N_t^{act} \right)^{1+\eta} \right) = Welfare^{hypo} \tag{14}$$

The results are presented in Table 6. The welfare losses from expectational biases of firms in this simple model economy are small. The welfare losses range from 0.01 percent to 0.11 percent. The welfare costs under the broad definition of the production expectation error are higher than those under the narrow definition. The main reason for this is that there are more optimist and pessimist firms under the broad definition. But even then the welfare

Table 6: Welfare Losses Associated with Biased Expectations

Type of Expectation Error	Welfare Loss in %	Consumption Equivalent in %
$FE_{i,t}^{narrow}$	0.0154	0.0118
$FE_{i,t}^{broad}$	0.1481	0.1103

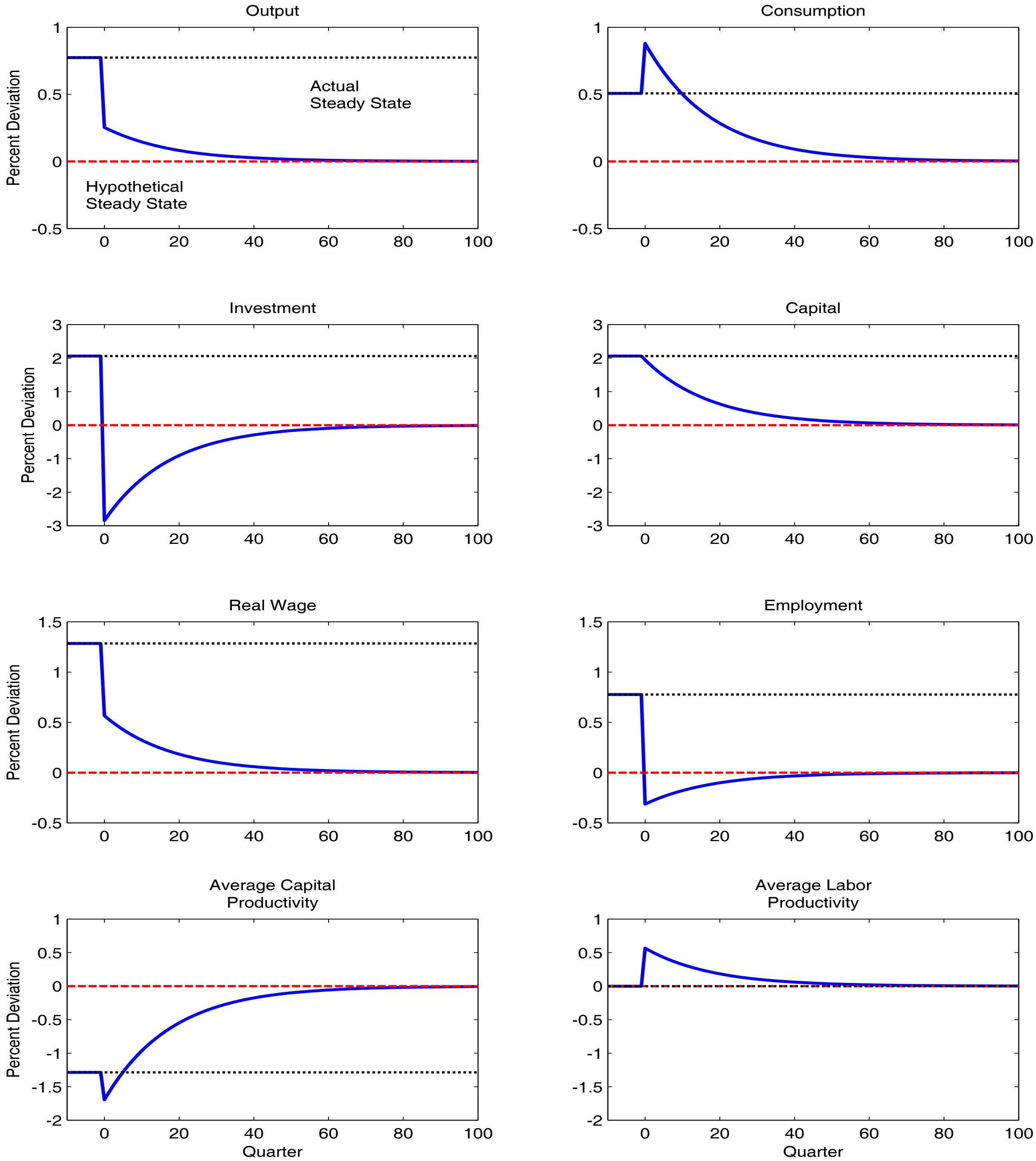
Notes: The welfare loss is computed as the percent difference of $Welfare^{act}$ and $Welfare^{hypo}$. The third column shows the welfare loss expressed in terms of consumption equivalents, according to equation (14). To compute this number we divide $\overline{C}$ by the steady state consumption level of the actual economy with expectational biases.

loss in terms of consumption amounts to only roughly 0.1 percent, a number comparable to conventional estimates of the costs of business cycle fluctuations (see Lucas, 1987, 2003).

Figure 3 presents the transition paths of major macroeconomic aggregates between the steady state with expectational biases and the hypothetical steady state with only realist firms for the broad definition of the production expectation errors, $FE_{i,t}^{broad}$.[14] Notice first that the hypothetical steady state with only realist firms features lower output, consumption, investment, employment and real wages, albeit higher average capital productivity and labor productivity. Resources, in particular capital, are more efficiently allocated in the hypothetical steady state. In contrast, in the steady state with expectational biases optimist firms dominate and the economy has too much capital accumulated and works too much. This is where the transition analysis as opposed to a mere steady state comparison is important. After the elimination of all expectational biases the economy enjoys a boom in consumption and leisure on impact which ultimately leads to the welfare improvements documented in Table 6.

[14] In Appendix E we also show the transition paths for the narrow definition of quantitative expectation errors, $FE_{i,t}^{narrow}$.

Figure 3: Transition Paths for the Case of $FE_{i,t}^{broad}$



Notes: This figure shows the transition paths of several macroeconomics variables for the case of $FE_{i,t}^{broad}$. These dynamic responses are expressed as percentage deviations from the steady state of the hypothetical economy without expectational biases.

5 Robustness Checks

This section provides a series of robustness checks to our baseline welfare calculations. All robustness checks change one feature of the calibration at a time, relative to the baseline scenario. First, we reconsider the definition of optimistic and pessimistic firms. In the baseline case we defined expectational biases by exploiting firm histories of expectation errors, i.e. we defined expectationally biased firms statistically as firms whose average production expectation error was significantly different from zero, given their history of production expectation errors. An alternative is to define optimists as having an average expectation error below the 10th percentile of the average production error distribution and a pessimist as having an average expectation error above the 90th percentile. We also consider 25/75th percentile thresholds.[15] The second and third panel in Table 7 show that in this case welfare losses are somewhat higher, but their overall magnitude is comparable to our baseline estimates.

The next robustness check concerns the calibration of ρ_1, ρ_2 and ρ_3. In the baseline scenario we calibrated these transition probabilities by using the qualitative production index $REALIZ_{i,t}$. In particular, we used the signs of this index for calibration. Now we replace it by $sign(\Delta \log u_{i,t})$, which is derived from the quantitative production changes. This modification in the calibration strategy yields somewhat higher welfare costs for both types of expectation errors. In particular, under the broad definition the welfare loss in consumption increases to almost 0.18 percent. Nonetheless, these numbers are of the same order of magnitude as our baseline results.

We also check robustness with respect to the number of observations that we require a firm to have in order to compute an average production forecast error. Instead of 32 observations we use a threshold of 16 observations or four years of quarterly quantitative production errors. This gives us a larger cross section of firms at the cost of having more firms with shorter histories in our sample. In the case of $FE_{i,t}^{narrow}$ the welfare losses get somewhat higher, but they are still in line with our baseline estimates.

In the next robustness check we do not clean our sample from "inconsistent" statements regarding quantitative and qualitative production changes. After all, these inconsistent statements might indicate some form of irrationality. Thus, the removal of these observations could bias the welfare cost estimates downward. If we repeat our analysis without eliminating these observations, we, unsurprisingly, observe slight increases in all welfare losses. But their order of magnitude remains unchanged.

In our final robustness check we relax the symmetry assumption built into the transition

[15] We provide the values of ρ_1, ρ_2, ρ_3, ϵ and ϕ for these and other robustness checks in Appendix F. For some cases ϕ takes on corner solutions that cannot match the data moments perfectly.

Table 7: ROBUSTNESS CHECKS - WELFARE LOSSES

Type of Expectation Error	**Welfare Loss in %**	**Consumption Equivalent in %**
Baseline Results		
$FE_{i,t}^{narrow}$	0.0154	0.0118
$FE_{i,t}^{broad}$	0.1481	0.1103
10% and 90% Percentile		
$FE_{i,t}^{narrow}$	0.0566	0.0434
$FE_{i,t}^{broad}$	0.1703	0.1264
25% and 75% Percentile		
$FE_{i,t}^{narrow}$	0.0912	0.0701
$FE_{i,t}^{broad}$	0.1553	0.1157
Quantitative Production Changes		
$FE_{i,t}^{narrow}$	0.0187	0.0143
$FE_{i,t}^{broad}$	0.2352	0.1786
16 Observations of Production Expectation Errors		
$FE_{i,t}^{narrow}$	0.0383	0.0291
$FE_{i,t}^{broad}$	0.1335	0.0992
Including "Inconsistent" Production Change Statements		
$FE_{i,t}^{narrow}$	0.0234	0.0173
$FE_{i,t}^{broad}$	0.1524	0.1119
Asymmetric Transition Matrix P^{obj}		
$FE_{i,t}^{narrow}$	0.0131	0.0096
$FE_{i,t}^{broad}$	0.1607	0.1101

Notes: See notes to Table 6. This table shows the welfare cost estimates of expectational biases for the baseline case and robustness checks.

matrix P_{opt}. This modification allows for different transitions probabilities. P_{opt} is therefore defined as follows:

$$P^{obj} = \begin{pmatrix} \rho_{1,u} & \rho_{2,u} & 1-\rho_{1,u}-\rho_{2,u} \\ \rho_{3,u} & 1-\rho_{3,u}-\rho_{3,l} & \rho_{3,l} \\ 1-\rho_{1,l}-\rho_{2,l} & \rho_{2,l} & \rho_{1,l} \end{pmatrix}.$$

To calibrate $\rho_{3,u}$ ($\rho_{3,l}$) we compute for each quarter the fraction of firms with an increase (decrease) in upcoming production , i.e. $REALIZ_{i,t+3}$ is greater (smaller) than zero, conditional on a normal current business situation. The time series average of these fractions provides an estimate of $\rho_{3,u}$ ($\rho_{3,l}$).[16] We determine $\rho_{1,u}$ ($\rho_{1,l}$) by computing the fractions

[16] As before we use only those firms that pass the outlier and consistency test (Q1 and Q5).

of firms that have no decrease (no increase) in their production level over the next three months, i.e. $REALIZ_{i,t+3}$ is greater or equal (smaller or equal) to zero, conditional on a good (bad) current business situation. Finally, we take the average of the time-series and get $\rho_{1,u}$ ($\rho_{1,l}$). To calibrate $\rho_{2,u}$ and $\rho_{2,l}$ we compute the two unconditional quarterly fractions of firms which either increase or decrease their production level over the upcoming quarter, i.e. $REALIZ_{i,t+3}$ is either greater or smaller than zero, but not equal to zero. The time-series averages of these two time series provide empirical moments that have to be matched by the model. Given $\rho_{1,u}$, $\rho_{1,l}$, $\rho_{3,u}$ and $\rho_{3,l}$ we find values for $\rho_{2,u}$ and $\rho_{2,l}$ that yield the same fractions of firms which either increase or decrease their economic state in the model. Table 8 summarizes the calibration results.

Table 8: Calibration: Asymmetric Transition Matrix P^{obj}

Calibration			
Parameter	Description	$FE_{i,t}^{narrow}$	$FE_{i,t}^{broad}$
$\rho_{1,u}$	Parameter Transition Matrix	0.8744	0.8463
$\rho_{1,l}$	Parameter Transition Matrix	0.8500	0.8513
$\rho_{2,u}$	Parameter Transition Matrix	0.1256	0.1537
$\rho_{2,l}$	Parameter Transition Matrix	0.0750	0.0743
$\rho_{3,u}$	Parameter Transition Matrix	0.2312	0.3005
$\rho_{3,l}$	Parameter Transition Matrix	0.1834	0.2316
ϵ	Parameter of Technology State	0.0881	0.1727
ϕ	Expectational Bias Parameter	0.1834	0.1580

With these parameter values we obtain the welfare losses summarized in the last panel of Table 7. It turns out that these results do not differ substantially from the baseline scenario. The economy experiences at most a welfare loss in consumption equivalents of about 0.1 percent.

6 Conclusion

This paper, using the micro data from the German IFO Business Climate Survey, constructs a panel data set of firms' quantitative one-quarter-ahead expectation errors with respect to their production. With this data set, we can gauge whether firms errors are systematic and thus biased towards optimism or pessimism. We find some degree of biased expectations, but for the large majority of firms we find realistic expectations in the sense that zero average expectation errors cannot be rejected.

We note that obviously our survey data have limitations and the derivation of production expectation errors is conditional on many assumptions. This calls for better survey data that ask for production changes and production change expectations directly, quantitatively, and consistently over many time periods. We still deem the question of the economic importance of expectation formation as important enough so as to make use of the best available, if less than perfect data to get a first answer to this question.

To do so we make use of the simplest possible neoclassical heterogeneous-firm model, where expectation errors play a role. Expectational biases lead to factor misallocations in the economy, and a welfare analysis will allow us to gauge the economic significance of such misallocations. We find that even when expectational errors are very broadly defined, the welfare costs of these misallocations are generally small, at the order of magnitude of conventional estimates for the welfare costs of business cycles.

We do, however, note that our model is somewhat simplistic and expect future research to compute welfare losses in more realistic environments. In this sense, we view the second half of the paper only as a first-pass, back-of-the-envelope-type calculation. We speculate that in economies with physical adjustment frictions to capital, financial frictions or endogenous growth elements larger welfare losses from expectational biases can be found. Future research can then make use of our empirical results for firms' average production errors to calibrate such models.

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Appendix

A Original German IFO-BCS Questions

Q 1 *"Sonderfragen: Die **Ausnutzung** unserer **Anlagen** zur Herstellung von XY (betriebsübliche Vollauslastung=100%) beträgt **gegenwärtig** bis zu ...%. "*

30	40	50	60	70	75	80	85	90	95	100	mehr als 100 % und zwar

Q 2 *"Erwartungen für die nächsten 3 Monate: **Beschäftigte** (nur inländische Betriebe) - Die Zahl der mit der Herstellung von XY beschäftigten Arbeitnehmer wird: zunehmen, etwa gleichbleiben, abnehmen."*

Q 3 *"Sonderfragen: Unter Berücksichtigung unseres gegenwärtigen Auftragsbestandes und des von uns in den nächsten 12 Monaten erwarteten Auftragseingangs halten wir unsere derzeitige **technische Kapazität** für XY für: mehr als ausreichend, ausreichend, nicht ausreichend. "*

Q 4 *"Erwartungen für die nächsten 3 Monate: Unsere inländische **Produktionstätigkeit** – ohne Berücksichtigung unterschiedlicher Monatslängen und saisonaler Schwankungen – bezüglich XY wird voraussichtlich: steigen, etwa gleich bleiben, abnehmen."*

Q 5 *"Tendenzen im vorangegangenen Monat: Unsere inländische **Produktionstätigkeit** – ohne Berücksichtigung unterschiedlicher Monatslängen und saisonaler Schwankungen – bezüglich XY ist: gestiegen, etwa gleich geblieben, gesunken."*

Q 6 *"Aktuelle Situation: Wir beurteilen unsere **Geschäftslage** für XY als: gut, befriedigend, schlecht."*

B Derivation of Quantitative Expectation Errors under General Production Expectations

We begin by defining the firm-specific activity variable $REALIZ_{i,t}$ as the sum of the Increase-instances minus the sum of the Decrease-instances in question Q5 over the three months going backward from t. $REALIZ_{i,t}$ can have seven possible values that live in the interval [-3,3]. The qualitative production expectation errors are then computed as follows:

Table 9: Possible Qualitative Expectation Errors

		$EXPERROR_{i,t}$
Expected $Increase_{t-3}$	$REALIZ_{i,t}>0$	0
Expected $Increase_{t-3}$	$REALIZ_{i,t} \leq 0$	$(REALIZ_{i,t} - 1)$
Expected $Unchanged_{t-3}$	$REALIZ_{i,t}>0$	$REALIZ_{i,t}$
Expected $Unchanged_{t-3}$	$REALIZ_{i,t} = 0$	0
Expected $Unchanged_{t-3}$	$REALIZ_{i,t}<0$	$REALIZ_{i,t}$
Expected $Decrease_{t-3}$	$REALIZ_{i,t}<0$	0
Expected $Decrease_{t-3}$	$REALIZ_{i,t} \geq 0$	$(REALIZ_{i,t} + 1)$

Notes: Rows refer to the qualitative expectations in month $t-3$ (Q4).

$EXPERROR_{i,t}$ ranges from $[-4, 4]$, where, for instance, -4 indicates a really negative forecast error: the company expected production to increase over the next three months, yet every single subsequent month production actually declined.[17]

Next we compute for all firms with a given value of $REALIZ_{i,t}$ in time t the average $\Delta \log u_{i,t}$, i.e. the cross-sectional average change in capacity utilization. Again, to ensure that we can treat utilization changes as production changes only those firms are considered that state three months before that their future employment levels will remain the same and that their technical production capacities are sufficient. We compute this mapping between $REALIZ_{i,t}$ and average production changes for each point in time.[18] Figure 4 illustrates the timing of survey questions that are used to compute this mapping. In Table 10 we provide summary statistics of the quantitative production changes over the entire pooled cross-section, separately for the seven values $REALIZ_{i,t}$ can adopt. Finally, Figure 5 depicts the time series of the average $\Delta \log y_{i,t}^{act}$ for each value of $REALIZ_{i,t}$. It shows, for example, that firms with $REALIZ_{i,t} = 1$ in the first quarter of 1980 have an average increase in production of approximately 5 percent.

[17] See Bachmann, Elstner, and Sims (2013), where this procedure for defining qualitative expectation errors has been introduced for the IFO-BCS. For similar ideas see Nerlove (1983) and Müller and Köberl (2007).

[18] We also considered a firm-size-specific and an industry-specific mapping, without much change to results.

Figure 4: Mapping between Qualitative and Quantitative Production Changes

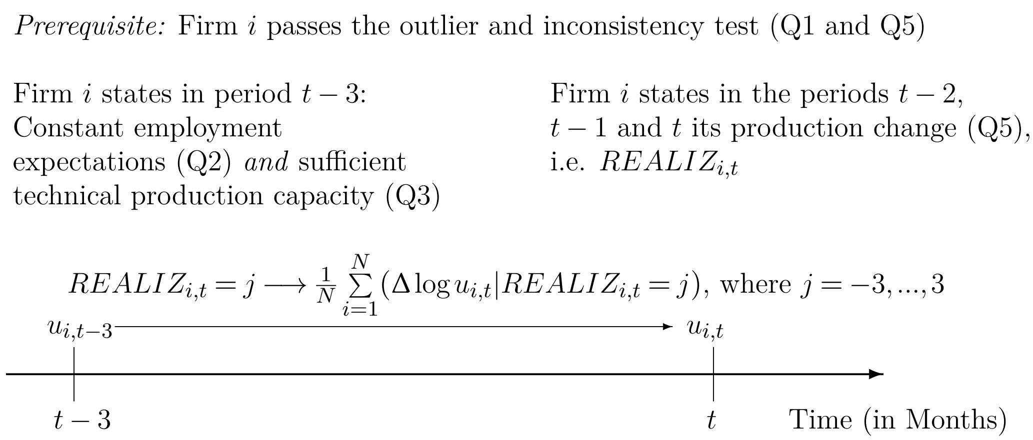
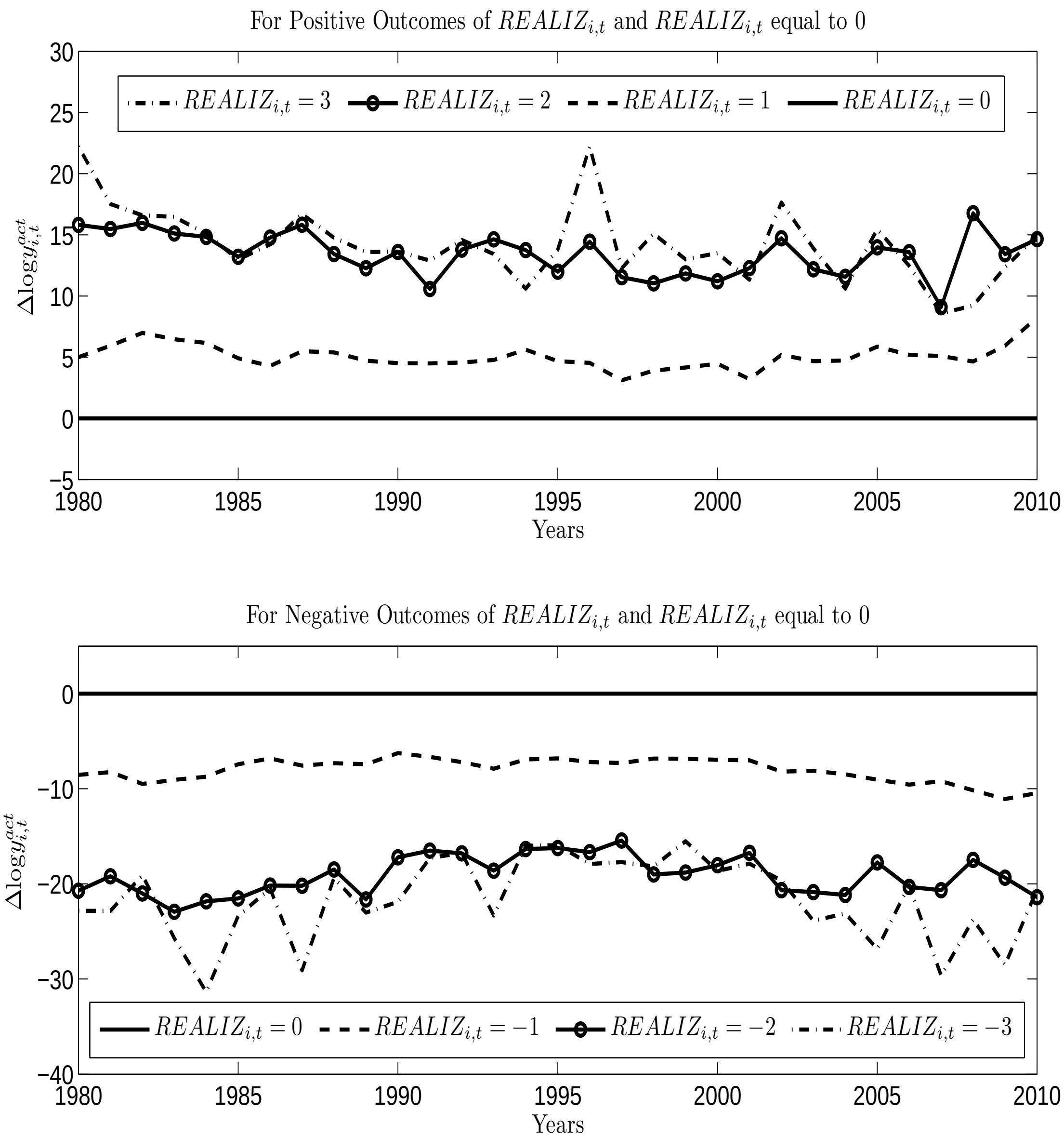


Table 10: Qualitative and Quantitative Production Changes – Summary Statistics for the Pooled Cross-Section

$REALIZ_{i,t}$	Number of Observations	Mean of $\Delta \log y_{i,t}^{act}$	Standard Deviation of $\Delta \log y_{i,t}^{act}$
3	1,786 (1.7%)	0.1426	0.1378
2	3,950 (3.7%)	0.1356	0.1288
1	19,285 (17.9%)	0.0510	0.1165
0	55,711 (51.7%)	-0.0006	0.0618
-1	19,147 (17.8%)	-0.0800	0.1532
-2	5,461 (5.1%)	-0.1950	0.1824
-3	2,423 (2.2%)	-0.2158	0.1995
All	107,763 (100.0%)	-0.0128	0.1323

Notes: This table provides summary statistics of the quantitative production changes over the entire pooled cross-section for the values $REALIZ_{i,t}$ can adopt.

Figure 5: Mapping of $REALIZ_{i,t}$ into Quantitative Production Changes



Notes: This figure shows for each possible value of $REALIZ_{i,t}$ the average $\Delta \log y_{i,t}^{act}$ of all firms with a given value for $REALIZ_{i,t}$. For better readability, the quarterly values of $\Delta \log y_{i,t}^{act}$ have been averaged to annual numbers. The upper panel shows the results for positive outcomes of $REALIZ_{i,t}$ and $REALIZ_{i,t}$ equal to zero. The lower panel does the results for negative outcomes of $REALIZ_{i,t}$ and $REALIZ_{i,t}$ equal to zero. The cross-sectional average $\Delta \log y_{i,t}^{act}$ of $REALIZ_{i,t} = 0$ has been subtracted from all time series shown in the figure.

We subject this mapping to a couple of plausibility tests. The first plausibility test can be gathered from Figure 5, which shows that the average $\Delta \log y_{i,t}^{act}$ for $REALIZ_{i,t} = 1$ is positive and lies strictly below the average $\Delta \log y_{i,t}^{act}$ for $REALIZ_{i,t} = 2$, analogously for $REALIZ_{i,t} = -1$ and $REALIZ_{i,t} = -2$. As regards the relative position of the assigned values for $REALIZ_{i,t} = 3$ (and $REALIZ_{i,t} = -3$) vis-a-vis $REALIZ_{i,t} = 2$ ($REALIZ_{i,t} = -2$) we note that only very few observations fall into the $REALIZ_{i,t} = 3$ ($REALIZ_{i,t} = -3$) category (see Table 10), so that we will invariably measure the average $\Delta \log y_{i,t}^{act}$ for the two extreme categories with noise only, even though for most time periods the assigned value for $REALIZ_{i,t} = 3$ lies above the one for $REALIZ_{i,t} = 2$, and analogously for $REALIZ_{i,t} = -3$ and $REALIZ_{i,t} = -2$.

Next, the pooled Spearman correlation coefficient between $REALIZ_{i,t}$ and $\Delta \log u_{i,t}$ for firms with constant employment and technical capacity expectations is 0.72. The pooled Kendall's tau between $sign(REALIZ_{i,t})$ and $sign(\Delta \log u_{i,t})$ for the same sample is 0.66. This means that on average the qualitative production change index based on $REALIZ_{i,t}$ is a good proxy for the quantitative production change based on $\Delta \log u_{i,t}$.

So far, all we have constructed is a mapping between qualitative production changes and the average quantitative production changes associated with them. We have also established that this mapping gives prima facie plausible results. Our ultimate goal, however, is to construct quantitative production expectation *errors* for firms where we only have qualitative production expectations, i.e. those firms that answer either 'Increase' or 'Decrease' to Q4. The basic idea is to use the mapping established for production changes also for production expectation errors.

For firms with constant production expectations we have a simple plausibility test for this procedure. Suppose we know with $FE\_BCS_{i,t}^{narrow}$ the "true" quantitative production expectation error for the firms with constant production expectations. Of course, we can also use the outlined mapping strategy for these firms, in which case the average percentage change in capacity utilization for a given $REALIZ_{i,t}$ would be an alternative (to $FE\_BCS_{i,t}^{narrow}$) estimate for their production expectation error. We can then compare both estimates.

Indeed, the time series correlation coefficients between the cross-sectional averages and, respectively, the cross-sectional standard deviations for these two estimates of expectation errors are high: 0.97 for the average expectation error and 0.83 for the standard deviation. This means that *over time* the mapping strategy captures the first and second moment of the quantitative production expectation error distribution rather well. However, *on average* the "true" production expectation errors, based on $FE\_BCS_{i,t}^{narrow}$ for the firms with constant production expectations, are more disperse than those based on the mapping strategy.

Since the time series behavior of the cross-sectional standard deviation is very similar, we view this essentially as a scaling problem, resulting from the discretization of expectation errors in the mapping strategy. As a consequence, we will scale the quantitative production expectation error values that the qualitative expectation errors $EXPERROR_{i,t}$ are mapped into by a constant to recover the average dispersion of production expectation errors based on $FE\_BCS_{i,t}^{narrow}$.[19]

The last step of the procedure is then the mapping of qualitative production expectation errors into quantitative production expectation errors. This is simply done by assigning to each value of $EXPERROR_{i,t}$ the normalized and scaled quantitative counterpart of $REALIZ_{i,t}$. In other words: if firm i in I/1980 answered 'Increase' or 'Decrease' to Q4[20] and had $EXPERROR_{i,II/1980} = 1$, then we would assign this firm the following quantitative production expectation error, $FE\_BCS_{i,t}^{broad}$:

$$\left(\frac{1}{N}\sum_{i=1}^{N}(\Delta \log u_{i,II/1980} | REALIZ_{i,II/1980} = 1) - \frac{1}{N}\sum_{i=1}^{N}(\Delta \log u_{i,II/1980} | REALIZ_{i,II/1980} = 0)\right) \times 1.7.$$

The extreme cases of $EXPERROR_{i,t} = 4$ and $EXPERROR_{i,t} = -4$, are added through extrapolation.[21]

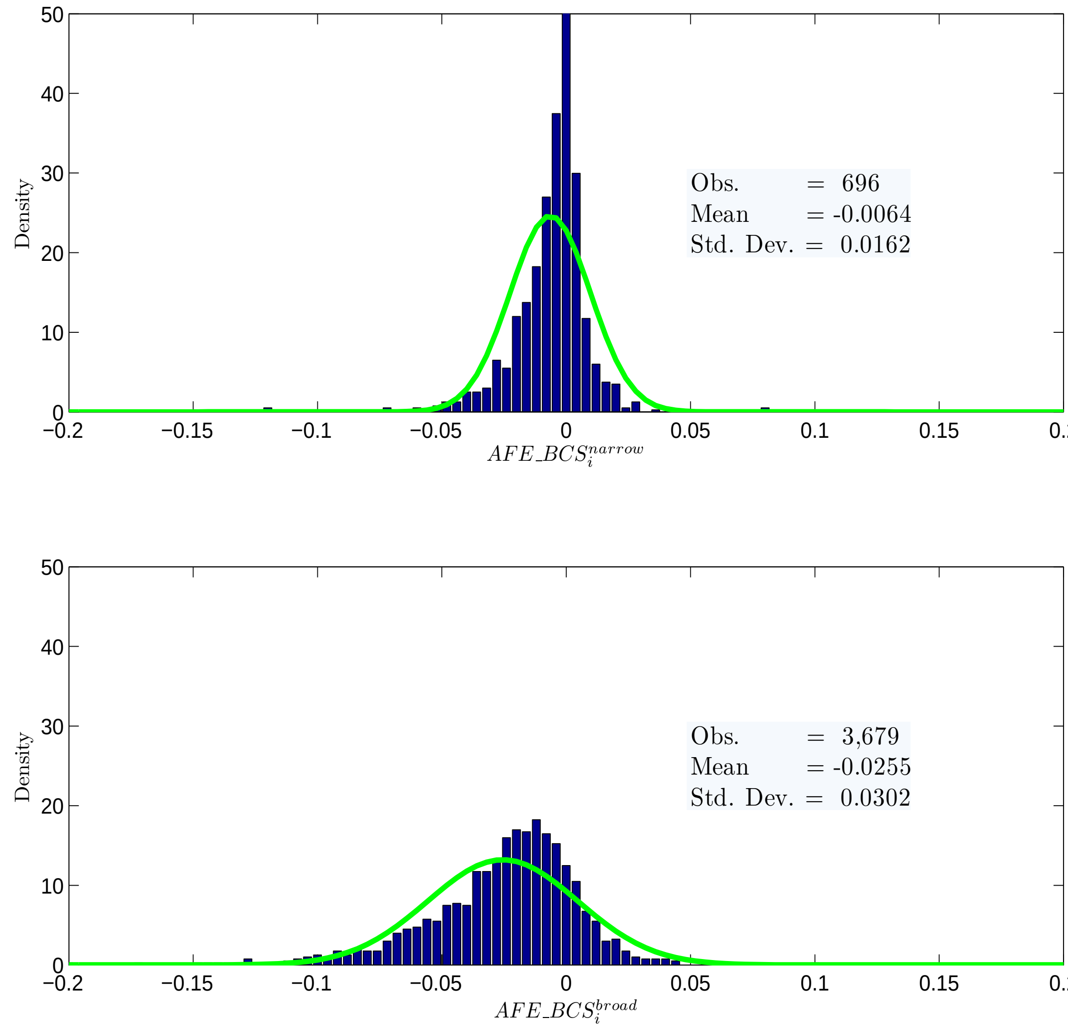
[19] This scaling constant 1.7 and is calculated by dividing the time average of the cross-sectional standard deviations of $FE\_BCS_{i,t}^{narrow}$ by the corresponding value derived from the mapping procedure on the same subset of observations.

[20] For firms with constant production expectations we continue to use $FE\_BCS_{i,t}^{narrow}$.

[21] The extrapolation procedure tries to capture the change in the differences of the quantitative counterparts of $REALIZ_{i,t}$, as displayed in Table 10. It concerns only 0.25 percent of all observations. Neglecting these extreme values in the welfare analysis would not alter the results.

C Firm-Specific Average Production Expectation Errors - Histograms

Figure 6: Histograms of the Firm-Specific Average Production Expectation Errors - Baseline Cases



Notes: This figure shows the histograms of the distributions of the firm-specific means of $FE\_BCS_{i,t}^{narrow}$ and $FE\_BCS_{i,t}^{broad}$ together with the normal distribution (green line) with the same means and standard deviations as the expectation error distributions.

D Firm-Specific Average Production Expectation Errors - Robustness

Table 11: Firm-Specific Average Production Expectation Errors - Including "Inconsistent" Production Change Statements

Statistics	$AFE\_BCS_i^{narrow}$	$AFE\_BCS_i^{broad}$
Obs	1,677	4,244
Mean	-0.0070	-0.0304
Std.Dev.	0.0172	0.0312
Percentiles		
5th	-0.0350	-0.0876
10th	-0.0245	-0.0698
25th	-0.0125	-0.0448
50th	-0.0045	-0.0251
75th	0.0012	-0.0100
90th	0.0074	0.0012
95th	0.0122	0.0086
# Optimists	45 (2.7%)	1,547 (36.5%)
# Pessimists	2 (0.1%)	23 (0.5%)
# Realists	1,630 (97.2%)	2,674 (63.0%)

Notes: This table provides a summary of the distributions of $AFE\_BCS_i^{narrow}$ and $AFE\_BCS_i^{broad}$. In contrast to the baseline scenario we also include firm-quarter observations where firms have "inconsistent" production change statements. In the last three rows we report the number of firms which are classified as optimists, pessimists and realists, respectively. We define optimistic firms as those firms which feature a negative average expectation error that is significantly different from zero, at the five percent level. Pessimistic firms are defined as those firms with a positive average expectation error that is significantly different from zero, at the five percent level.

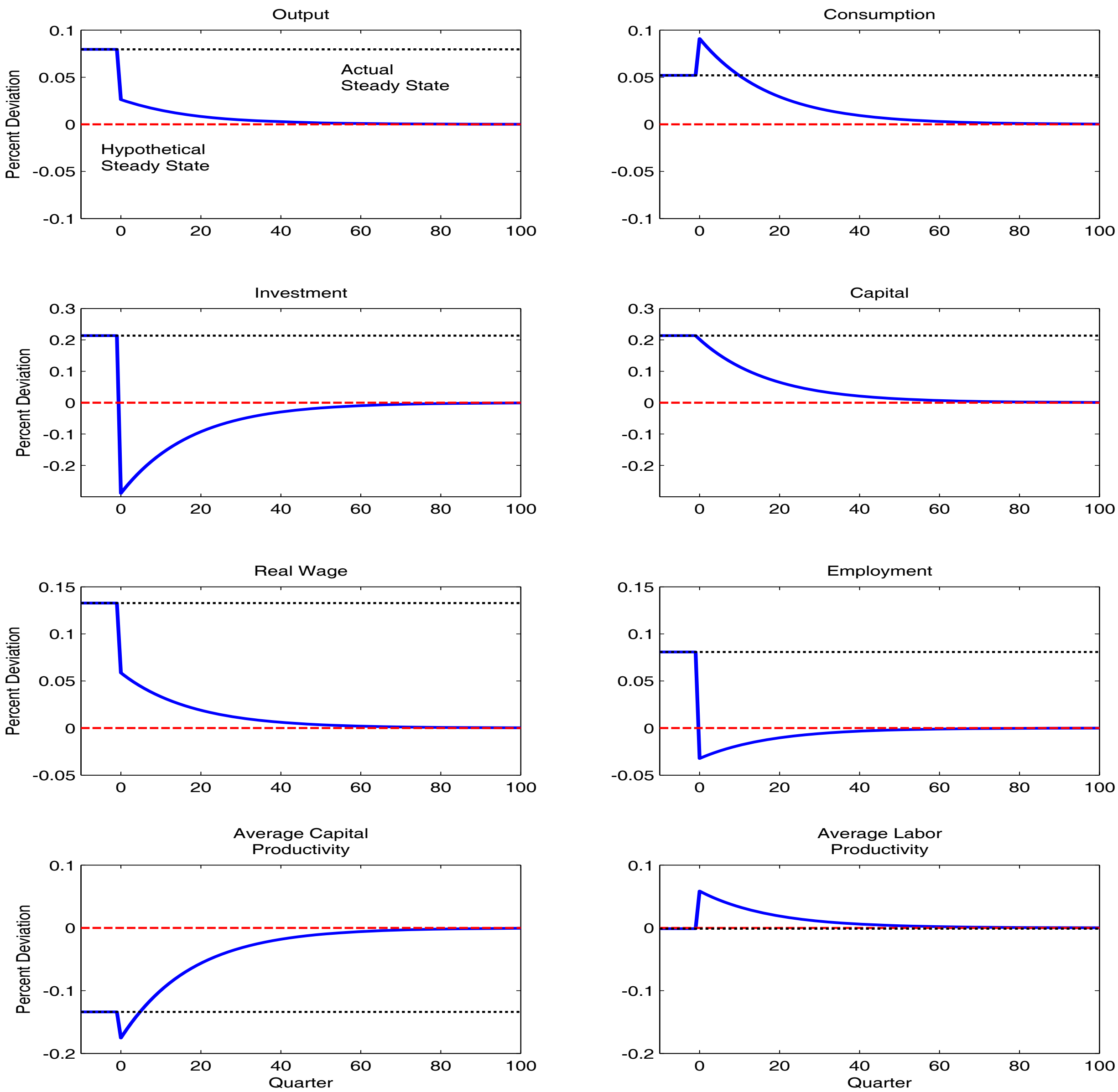
Table 12: Firm-Specific Average Production Expectation Errors - 16 Observation Threshold

Statistics	$AFE\_BCS_i^{narrow}$	$AFE\_BCS_i^{broad}$
Obs	2,140	5,438
Mean	-0.0112	-0.0278
Std.Dev.	0.0265	0.0363
Percentiles		
5th	-0.0574	-0.0945
10th	-0.0383	-0.0732
25th	-0.0182	-0.0443
50th	-0.0049	-0.0215
75th	0.0020	-0.0048
90th	0.0101	0.0091
95th	0.0171	0.0190
# Optimists	118 (5.5%)	1,528 (28.1%)
# Pessimists	13 (0.6%)	77 (1.4%)
# Realists	2,009 (93.9%)	3,833 (70.5%)

Notes: This table provides a summary of the distributions of $AFE\_BCS_i^{narrow}$ and $AFE\_BCS_i^{broad}$. In contrast to the baseline scenario we restrict our sample to firms that have at least 16 quarterly observations of expectation errors. In the last three rows we report the number of firms which are classified as optimists, pessimists and realists, respectively. We define optimistic firms as those firms which feature a negative average expectation error that is significantly different from zero, at the five percent level. Pessimistic firms are defined as those firms with a positive average expectation error that is significantly different from zero, at the five percent level.

E Transition Paths for the Case of $FE_{i,t}^{narrow}$

Figure 7: Transition Paths for the Case of $FE_{i,t}^{narrow}$



Notes: This figure shows the transition paths of several macroeconomics variables for the case of $FE_{i,t}^{narrow}$. These dynamic responses are expressed as percentage deviations from the steady state of the hypothetical economy without expectational biases.

F Robustness Checks - Calibration

Table 13: Calibration Robustness Checks

	Parameter Transition Matrix ρ_1	Parameter Transition Matrix ρ_2	Parameter Transition Matrix ρ_3	Parameter Technology State ϵ	Expectational Bias Parameter ϕ	AR(1)-coefficient	S.E. of Regress.
Baseline Results							
$FE_{i,t}^{narrow}$	0.8622	0.1378	0.2073	0.0959	0.1486	0.8619	0.0421
$FE_{i,t}^{broad}$	0.8488	0.1512	0.2661	0.1914	0.1068	0.8485	0.0893
Robustness Check - 10th and 90th Percentile							
$FE_{i,t}^{narrow}$	0.8622	0.1378	0.2073	0.0764	0.2073	0.8622	0.0335
$FE_{i,t}^{broad}$	0.8488	0.1512	0.2661	0.2011	0.1348	0.8489	0.0937
Robustness Check - 25th and 75th Percentile							
$FE_{i,t}^{narrow}$	0.8622	0.1378	0.2073	0.0616	0.2073	0.8618	0.0270
$FE_{i,t}^{broad}$	0.8488	0.1512	0.2661	0.1921	0.0875	0.8490	0.0895
Robustness Check - Quantitative Production Changes							
$FE_{i,t}^{narrow}$	0.8487	0.1381	0.2990	0.0802	0.1974	0.8354	0.0397
$FE_{i,t}^{broad}$	0.8050	0.1950	0.3981	0.1504	0.1746	0.8050	0.0800
Robustness Check - At Least 16 Observations of Production Expectation Errors							
$FE_{i,t}^{narrow}$	0.8537	0.1462	0.2436	0.1195	0.1889	0.8537	0.0546
$FE_{i,t}^{broad}$	0.8488	0.1511	0.2727	0.1980	0.1039	0.8498	0.0926
Robustness Check - Including "Inconsistent" Production Change Statements							
$FE_{i,t}^{narrow}$	0.8610	0.1389	0.2299	0.1888	0.1340	0.8611	0.0841
$FE_{i,t}^{broad}$	0.8509	0.1490	0.2625	0.2214	0.0915	0.8509	0.1026

Notes: This table provides the values of ρ_1, ρ_2, ρ_3, ϵ and ϕ for the robustness checks. The next to last column displays the average of the estimated 100 AR(1)-coefficients for the simulated Markov chains resulting from these parameter choices (see notes to Table 5). The last column shows the average of the standard errors of these regressions. Each Markov chain has been simulated over 20,000 observations.