What Drives Aggregate Investment? Evidence from German Survey Data

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Abstract

The Ifo Investment Survey (IS) asks firms in the German manufacturing sector about the importance of technical factors, sales, finance, profit expectations, and macroeconomic policy for their investment activity in a given year. Using the survey responses to these questions, we construct measures of aggregate technology and non-technology shocks to quantify their contributions to aggregate investment dynamics. We find that 1) consistent with neoclassical models, technical factors on average are the most important investment determinant; 2) prior to the Great Recession, at most one third of the variance of the aggregate investment growth rate can be explained by technical factors; we also find suggestive evidence that demand shocks interpreted as sentiment shocks explain the largest fraction of regular year-to-year investment growth fluctuations; 3) perhaps surprisingly, including data from the Great Recession, we find that a lack of the typically positive influence of technical factors makes them more important in explaining the (negative) aggregate investment growth rate during that time.

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1 Introduction

There is considerable disagreement among macroeconomists about the contribution of technology shocks to aggregate fluctuations. While some authors report evidence in favor (Christiano et al., 2003; Fisher, 2006; Alexopoulos, 2011), others call the idea of technology-driven business cycles into question (Hall, 1997; Galí, 1999; Shea, 1998; Francis and Ramey, 2005; Basu et al., 2006). Some of this disagreement is the result of different ways to construct technology shocks: because of their unobserved nature, macroeconomists have to resort to various empirical approaches to measure them, each with its underlying assumptions that can be the target of critique. For example, the "purified" technology measure by Basu et al. (2006) - basically the Solow residual accounting for non-technological effects such as varying capacity utilization, non-constant returns to scale, and aggregation effects - might be prone to "incomplete cleansing"; see Alexopoulos (2011, p.1146). The other often-used technology measure, obtained from long-run restrictions in vector autoregressions (VARs), can be contaminated by other, possibly also unobserved, exogenous shocks, for example tax shocks or preference shocks, or made invalid by heterogeneous factor inputs into the aggregate production function; see, respectively, Uhlig (2004) and Bocola et al. (2014).

This paper pursues an alternative measurement procedure. Using unique data from the Ifo Investment Survey (IS) about firm-level capital expenditures in the West German manufacturing sector, and – this is the novel contribution of this paper – the subjective effects of several investment determinants on capital expenditures reported by decision-makers in these firms, we propose a survey-based, narrative approach to estimating shocks. The paper in the literature closest in spirit to our approach is Alexopoulos (2011), which uses industry publications to identify technological innovations. Specifically, the IS asks firms about the importance of technical factors, sales, finance, profit expectations, and macroeconomic policy for their investment decisions in a given year. Using the survey responses to these questions, we first construct aggregate index measures of technological and non-technological investment determinants in the manufacturing sector (henceforth aggregate investment de-

terminant indices). Next, we recover orthogonal aggregate technology and non-technology innovations to these indices. We finally compute the relative contributions of these orthogonalized aggregate shocks to the fluctuations of aggregate manufacturing investment growth (henceforth aggregate investment growth).

We find that, consistent with neoclassical models, on average over time technical factors are the most important investment determinant. When we restrict our analysis to the pre-Great Recession era, we find that technical factors can also explain a significant fraction of the business cycle fluctuations of investment: we estimate a contribution of approximately one third to the fluctuations of aggregate investment growth in the empirical specification that is most favorable to the technology-driven business cycle hypothesis. This means that technical factors are important to explain aggregate investment, but most strongly for investment on average and somewhat less so for investment fluctuations. These findings are robust to disaggregating the data at the two-digit industry level and by German states.

In addition, when we impose more structure on the empirical model, we find that what we interpret as demand shocks accounts for approximately 50 percent of the short-run fluctuations in aggregate investment growth. We provide suggestive evidence that these demand shocks can, for the most part, be interpreted as sentiment or confidence shocks.[1] Perhaps surprisingly, including data from the Great Recession, we find that a lack of the typically positive influence of technical factors makes them more important in explaining the (negative) aggregate investment growth rate during that time. As we will argue, this is consistent with the view of negative technology shocks as the slowing or temporary absence of technological progress.

Historical decompositions also reveal an interesting and complex narrative of German

[1] Note that our results are not inconsistent with a broader interpretation of the real business cycle idea that stresses the importance of changes in aggregate productivity for aggregate fluctuations. Rather, our results mean that measured aggregate productivity shocks may not only have to do with technological factors in a narrow sense, but also capture other determinants of aggregate productivity. A recent literature has microfounded the idea of demand- (Bai et al. (2012)) and sentiment-driven (Angeletos and La'O (2013)) aggregate productivity fluctuations. In this sense, our results do not invalidate the real business cycle idea per se, but point to elsewhere other than R&D and engineering departments for economists to find the main sources of measured aggregate productivity fluctuations.

macroeconomic history: while regular year-to-year investment fluctuations seem to be explained well by sentiment, a different picture arises for some major historical episodes in recent decades. For instance, while monetary policy seems unimportant for investment fluctuations for most of the sample period, 1989 to 2010, the post-reunification recession demand shock we find is likely a monetary policy shock, which is consistent with the historical narrative. The investment boom in the later half of the 1990s is related to technological factors (the worldwide "Tech"-boom); and the extended slump at the beginning of the 2000s can be attributed to a diminished importance of technological factors – Germany being the "sick man of Europe" –, while the boom afterwards looks like a positive sentiment shock. As mentioned above, the investment decline in the Great Recession has at least partially the signs of a (temporary) technological slowdown, on top of negative demand shocks.

We view the advantage of a survey-based approach towards identifying shocks in its putative directness: the survey respondents report whether their investment activity in a given year was influenced by, for instance, technical factors, and, if so, how strongly. Traditionally, there has been a branch of economics methodology that viewed subjective survey approaches, that is, asking economic agents what they did, what they expect and why they did something, with some scepticism. On the other hand, a growing group of economists has analyzed subjective survey data, mainly to study expectation formation and their rationality: Nerlove (1983), using business surveys from various countries, is a very early example, Bachmann and Elstner (2015) and Gennaioli et al. (2015) are more recent ones. Guiso and Parigi (1999) and Bachmann et al. (2013) have used expectation data from business surveys to study the impact of business uncertainty on economic activity. On the household side, Carroll and Dunn (1997), Souleles (2004), and Malmedier and Nagel (2016) are important examples, each with different research questions.

We view our approach as pushing one step further: if we can ask economic agents about their subjective expectations and gain useful economic insights, why not ask them about their subjective reasons for carrying out a particular economic action and use the answers for

economic analysis? In this regard, our approach is similar to other narrative methodologies that have been used in empirical macroeconomics to study the effects of macroeconomic policies (see Romer and Romer, 2004, 2010). Indeed, one of the contributions of this paper is to show that at least in the aggregate as well as for certain disaggregate investment growth rates the investment determinants from the IS have remarkable explanatory power. Finally, we view our survey-based approach to identifying macroeconomic shocks as complementary to the aforementioned existing approaches. Each of them has to make assumptions, and thus has drawbacks; one of our drawbacks is that we cannot strictly distinguish between neutral and investment-specific technology shocks, though we provide some suggestive evidence against the importance of investment-specific technology shocks. This, however, speaks for a multi-pronged approach to which we hope to add with this paper.

The remainder of this paper is organized as follows. Section 2 introduces the survey data and presents the aggregate investment determinant indices. We also assess in some detail whether the survey data capture the economic concepts they are supposed to measure. Section 3 lays out the empirical model for estimating the contribution of the aggregate investment determinants to aggregate investment growth fluctuations, and motivates the identifying assumptions. Section 4 presents the results, both for the manufacturing sector and disaggregated at the two-digit industry level and by German states. Section 5 summarizes the main findings and concludes.

2 The Survey Data

2.1 The Ifo Investment Survey (IS)

The IS is a semi-annual survey for the German manufacturing sector,[2] carried out in the spring and fall by the Ifo Institute since 1955. Its main purpose is to provide firm-level quantitative capital expenditure data and future investment plans for a panel of firms at an

[2]The mining sector is also included, though it is very small relative to manufacturing proper.

annual frequency. In addition, since 1989 and in the fall installment of the survey, it asks firms about the qualitative and subjective effects of several investment determinants on their capital expenditures in the current year. We have access to the micro data until 2010. Our maximum sample period therefore goes from 1989 to 2010, though we carry out our baseline analysis on the sample from 1989 to 2008. That is, we first exclude the Great Recession, in order to identify the more regular year-to-year sources of aggregate investment fluctuations, and bring the Great Recession back into focus later. We also only use the West German part of the data, because the survey questionnaire for East German firms is different and much less consistent over the years compared to that for West German firms.

The main advantages of the IS data are its high number of respondents, counting on average roughly 1,500 firms per year in our sample; that it provides quantitative firm-specific capital expenditure data; and the information about qualitative and subjective investment determinants, along with a host of other information about firm-level investment activities that we use to cross-validate the content of the subjective investment determinants. The subjective investment determinants are a rather unique feature of the IS. Moreover, aggregate investment growth implied by the survey micro data is highly correlated (0.91) with West German manufacturing investment growth data from the Federal Statistical Office (see Figure 1), which means that our sample is representative of the universe of firms in the West German manufacturing sector.[3] The low frequency of the data, annual, and the relatively small number of observations thus available in the time dimension is a disadvantage.[4] Nevertheless, we note that the planning horizon of firms for investment typically spans a (fiscal) year, so the annual frequency of the data is not per se restrictive.

Specifically, we make use of the following two questions from the survey questionnaire:

[3]We note that this high correlation is not a mechanical result, as the IS data is not an input into the official investment numbers. National accounting investment data are based on a separate and administrative investment survey run by the Federal Statistical Agency, which does not ask about investment determinants.

[4]Our robustness checks using semi-aggregate data at the two-digit industry level and by German states mitigate this problem somewhat.

Q1. Gross Fixed Capital Formation in Fiscal Year *[Last Year]*

[Last Year] _____
(in 1000 Euro)

Q2. Investment Determinants *[This Year]*

Our investment activity in the Old Laender in *[This Year]* was positively/negatively affected by:

	[This Year]				
Investment Determinant	strongly positive influence	weakly positive influence	no influence	weakly negative influence	strongly negative influence
Sales Situation and Expectation	☐	☐	☐	☐	☐
Finance	☐	☐	☐	☐	☐
Profit Expectation	☐	☐	☐	☐	☐
Technical Factors	☐	☐	☐	☐	☐
Macro Policy Environment	☐	☐	☐	☐	☐
Other	☐	☐	☐	☐	☐
[Codification]	*[+2]*	*[+1]*	*[0]*	*[-1]*	*[-2]*

In **Q1** firms report their realized capital expenditures for the preceding year, which is asked in the spring and the fall surveys (except for the falls of 2002 and 2003). In **Q2**, which is asked only in the fall survey, firms give information about how several investment determinants have affected their investment activity in the current year. Specifically, the survey questionnaire asks firms about the effects of their sales situation and expectations, finance, profit expectations, technical factors, the macro policy environment, and other investment determinants on their capital expenditures.[5] The possible answers are: "strongly negative", "weakly negative", "no influence", "weakly positive", or "strongly positive". The respondent is asked to check one box for each investment determinant. We code the answers in the variables `Tech`, `Finance`, `Sales`, `Profit`, `Macro`, and `Other` that can take on the values -2 (strongly negative influence), -1 (weakly negative influence), 0 (no influence), +1 (weakly positive influence), or +2 (strongly positive influence).[6]

[5] The survey guidelines for the investment determinants are available in the Appendix.

[6] The main results are quantitatively very similar if we use a concave (square root) or convex (quadratic) quantification scheme instead.

We only consider firm-year observations where the investment growth rate and at least one investment determinant are observable. Of course, we sync the answers to **Q1** and **Q2** in such a way that the investment determinants of a given year are paired with the investment activity of that same year. Our baseline sample 1989-2008 is based on 30,561 firm-year observations in total (33,247 for the extended sample 1989-2010).

2.2 Aggregation

Recall that our research question is about the sources of fluctuations in aggregate investment growth. We start our analysis by concentrating on aggregate dynamics due to common shocks that affect all firms in the economy. In order to measure these shocks, we first aggregate the survey responses through weighted averaging to compute what we call aggregate investment determinants. We do this for every investment determinant separately. Because of a law of large numbers argument, cross-sectional averaging eliminates idiosyncratic influences. The aggregate investment determinants are thus meant to capture the macroeconomic importance of a particular reason to invest in a given year.[7] From these investment determinants we then recover orthogonal aggregate shocks.[8] The fundamental identification assumption of our survey-based approach is that the firm-level survey responses contain information about the macroeconomic shocks that affect firms' investment decisions. The putative advantage of the survey-based approach is that the macroeconomic shocks are ultimately extracted from variables which are meant to directly measure the effect of, say, technology on capital expenditures. The recovered aggregate shocks are thus less likely to be confounded by other factors, and, to the extent that they might be, we can directly address the issue (see, for instance, Section 4.1.4 below).

[7] In addition, we found that due to the discrete nature of the survey responses for the investment determinants their explanatory power for investment growth at the firm level is rather weak, even though it is fairly substantial at the aggregate and semi-aggregate level.

[8] Our approach is thus related to structural factor-analytic methods; see Stock and Watson (2016) for a recent survey. In particular, the aggregate investment determinant indices can be interpreted as what Stock and Watson (2016) call named factors, i.e., they are linked to a specific reason to invest, estimated by cross-sectional averaging methods, which is a simple example of nonparametric estimation of factor models. We then identify orthogonal structural shocks from these factors.

In extensions, we also study semi-aggregate specifications at the two-digit industry level, and at the German state level. This allows us to gauge whether our aggregate results are driven by particular groups of firms or whether they capture macroeconomic phenomena. We find the latter.

Formally, let ΔI_t^{IFO} denote aggregate investment growth based on **Q1** of the Ifo Investment Survey, inv_{it} is firm i's investment in year t,[9] and N_t is the number of observations for which firm-level data is observable in years t and $t-1$. Define firm i's share in total investment at time t by $\omega_{it} = \frac{inv_{it}}{\sum_{i=1}^{N_t} inv_{it}}$. Then the aggregate investment growth rate, ΔI_t^{IFO}, is given by:

$$\Delta I_t^{IFO} = \sum_{i=1}^{N_t} \omega_{it-1} \frac{inv_{it} - inv_{it-1}}{inv_{it-1}} \tag{1}$$

Similarly, let x_{it} denote one of the six firm-level investment determinants defined above, ranging from -2 to +2. Then, for every investment determinant, we aggregate up to an investment determinant index, X_t, as follows:

$$X_t = \sum_{i=1}^{N_t} \omega_{it}\, x_{it} \tag{2}$$

With a slight abuse of notation, `Tech`, `Finance`, `Sales`, `Profit`, `Macro`, and `Other` may henceforth refer also to these aggregate investment determinant indices.

2.3 The Raw Data

In Figure 1 we compare the aggregate investment growth rate obtained from the Ifo Investment Survey data, ΔI_t^{IFO}, with that obtained from data for the West German manufacturing sector provided by the Federal Statistical Office, ΔI_t^{FSO}. The correlation coefficient between both series is 0.91.

[9] We average the fall and the spring capital expenditure data, whenever they are both available, because in a few circumstances they may slightly deviate from each other, and averaging thus helps mitigate measurement and reporting error. Otherwise we use whichever investment number, spring or fall, is available. The results are robust to using only the fall data. See for a detailed discussion of both data treatment procedures Bachmann et al. (2016).

Figure 2 plots the aggregate investment determinant indices over time. Two observations stand out. First, in contrast to the other investment determinant indices which often fluctuate around zero, the effect of technology on capital expenditures is positive throughout. In fact, as Panel C of Table 1 shows, technical factors are on average the most important subjective investment determinant. We view this as survey-based evidence for the neoclassical view that technological factors determine investment on average and in the long-run: the average value of `Tech` is 0.96, followed by `Sales`, which averages 0.63. By contrast, `Finance` and `Macro` are essentially zero on average. Second, the aggregate investment determinant indices are (imperfectly) correlated with each other and the business cycle. This is especially true for the Great Recession where all investment determinants decline.

Panel A of Table 1 shows the pairwise correlation coefficients of investment determinants for the baseline sample period from 1989 to 2008. For statistical inference, we generate 10,000 bootstrap estimates for the correlation coefficients by resampling overlapping moving blocks of a three-year length from the data. Next, we compute the statistical p-value as the fraction of bootstrap samples for which the correlation coefficient has the opposite sign of the point estimate. The correlation between `Tech`, `Sales`, `Finance`, `Profit` and `Macro` is always significant, positive, and in one case substantial: `Sales` and `Profit` have a correlation coefficient of approximately 0.94, which suggests that both variables capture a similar economic concept, and that `Profit` does not really seem to be influenced by firms' costs. The investment determinant index `Other` is not significantly correlated with any of the other variables.

The fact that some of these aggregated investment determinants are correlated is not surprising: for example, when there is a shock to financial intermediation in the economy, this may impact investment directly through standard finance effects, but also simultaneously through an aggregate demand effect from other firms and the households in this economy. It means, however, that we cannot interpret the investment determinants directly as shocks (hence the use of "investment determinants"). Nevertheless, we will argue below that given their interpretation as investment determinants we can use a simple recursive scheme to

extract orthogonal shocks that can be interpreted as technology and non-technology shocks. With additional assumptions we can go further and extract shocks that can be interpreted as aggregate demand shocks.

Panel B of Table 1 reports the correlations of the investment determinant indices with the aggregate investment growth rate, ΔI_t^{FSO}, from the official data. The correlation coefficient between `Tech` and ΔI_t^{FSO} is significant at 0.50. The correlation with the non-technological investment determinant indices – `Sales`, `Finance`, `Profit` and `Macro` – is also significant but much stronger. For example, the correlation coefficient between Sales and ΔI_t^{FSO} is 0.84. The category `Other` is not significantly correlated with the aggregate investment growth rate.[10]

From this simple correlational analysis we may already expect that technology shocks may be a significant, but perhaps not the main source of the regular time series variation of aggregate investment growth. This is also supported by the volatilities of these investment determinants: `Sales` and `Profit` are very volatile, unlike `Tech`, `Finance` and, to a certain extent, also `Macro`. As we have seen, the latter two also have little importance as investment determinants on average, which together means that we can expect them to play only a minor role in explaining aggregate investment fluctuations in Germany.

To sum up, this simple statistical analysis already reveals a lot that we later find confirmed in our econometric analysis: given its mean, `Tech` is important for investment on average, but given its relatively low volatility and milder correlation with aggregate investment growth unlikely the major regular driver for it; `Sales` and `Profit` are very volatile and highly correlated with investment growth (and with each other, which means they capture the same economic concept); `Finance` and `Macro` with their low means and low volatilities are not likely to be important for aggregate investment in Germany; and `Other` with its lack of correlation with either aggregate investment or any other investment determinant is an orthogonal catch-all category, again unlikely to be important for aggregate investment. This

[10] All these results are very similar with ΔI_t^{IFO} (not shown to conserve space). Also, the results in Panels A-C for the baseline sample 1989-2008 are very similar to the results for the extended sample 1989-2010 in Panels D-F of Table 1, though on the extended sample `Tech` gains somewhat in terms of cyclical importance.

suggests `Tech` and `Sales` as the main focus of our analysis, and justifies our initial distinction between technology versus non-technology shocks.

We conclude this section by separately investigating the behavior of the fraction of survey responses for each of the five answer categories – "strongly negative", "weakly negative", "no influence", "weakly positive", or "strongly positive" – and each of the six investment determinants: `Tech`, `Sales`, `Finance`, `Profit`, `Macro`, and `Other`, as shown in Figure 3. The top-left panel shows the fraction of survey answers in each category for `Tech`. There are essentially no firms that report a negative effect of technology on capital expenditures, consistent with the notion that technology shocks are rarely negative, even at the idiosyncratic level. Also, this panel reveals the anatomy of a potential negative aggregate technology shock around the Great Recession: the modal response flips from `Tech` being "weakly positive" to "no influence." This conforms with the conceptualisation of negative technology shocks as the slowing or temporary absence of technological progress for the typical firm.

By contrast, the modal responses for `Sales` and `Profit` fluctuate widely in the expected cyclical direction between "*weakly* positive" and "*strongly* negative," which is also consistent with business cycle asymmetries: recessions are brisk and severe, expansions smoother (see McKay and Reis (2008)). Furthermore, the panels for `Finance` and `Macro` confirm the "relatively unimportant"-diagnosis for these two investment determinants from above: almost always, even in severe recessions, more than half of the respondents attributed no role to them. This is, by and large, even true for `Finance` in the Great Recession: despite the importance of finance in the U.S. during that time, the Great Recession in Germany was not predominantly a financial crisis. Finally, the panel for `Other` shows that the IS is fairly exhaustive when it asks for investment determinants, because no other major investment determinant seems to have been omitted.

2.4 Economic Content

This subsection discusses the economic content of the aggregated investment determinant indices and provides plausibility checks as to whether they indeed capture the economic concepts that they are meant to measure.

`Tech`: We start with `Tech`. In addition to capital expenditure data and investment determinants, the IS also asks, again in the fall questionnaire, about the fraction of total investment expenditures which in that year went into increases in capacity, restructuring, rationalization, maintenance, and other types of capital expenditures. First, we want to guard against the following possibility, which would be an alternative – to the neoclassical view – interpretation for `Tech` being consistently and on average above zero: whenever firms have to replace and maintain their capital stock due to continual wear and tear they answer that technical factors played an important role in their investment decisions. To this end, we use the fraction of total investment in a given year that was undertaken for maintenance reasons, pool all these observations across years and firms, sort them and compute for each tercile the investment-weighted average of `Tech`. Table 2 displays the results: if anything, for firm-year observations that have a high-maintenance content in their investment activity, `Tech` plays a relatively lower role than for those with a low-maintenance content. The differences in conditional means across terciles are statistically significant at the 1% level. We therefore rule out that `Tech` merely captures the maintenance and replacement of existing capital.

We next perform the flip side to the test in Table 2, namely, whether `Tech` is positively correlated with other forms of investment, especially those that are plausibly related to technical innovations: restructuring and rationalization investment. We thus sum the shares for restructuring and rationalization investment and repeat the analysis that led to Table 2. Table 3 shows the results: the investment-weighted average of `Tech` increases monotonically with the share of investment that went into restructuring and rationalization. The differences in conditional means across terciles are statistically significant at the 1% level. This means

that for those firm-year observations that have a high innovation-content in their investment activity, `Tech` plays a relatively higher role, which makes it a plausible variable to identify technological innovations and their impact on investment decisions, a prerequisite for our narrative approach.

This interpretation is confirmed in our next test where we use another feature of the IS, which asked (in the spring questionnaire) until 2001 whether capital expenditures in the preceding year were targeted towards process innovations. The possible answers were "Yes" and "No". As before, we can pool all firm-year observations, compute the investment-weighted averages of `Tech` conditional on these two answers, and compare them. Table 4 shows the results: `Tech` plays a relatively larger role for the investment activity of those firms that had capital expenditures targeted towards process innovations. Again, the difference in conditional means is statistically significant at the 1% level.[11]

Eurostat provides a classification of three-digit manufacturing industries according to their technological intensity, defined as the ratio of industry R&D spending to value added.[12] Table 5 shows investment-weighted conditional means of the absolute value of `Tech`, conditional on three different R&D intensity classes, where we classify each firm-year observation into one of the three technology brackets provided by Eurostat.[13] While the results are less clean – we essentially assign to a firm the R&D intensity of its industry –, they nevertheless confirm the results using the IS firm-level data: the more technology-intensive a firm's industry is, the more important the role `Tech` plays in its investment activity on average.

Turning, finally, to some suggestive time series evidence, we see from Figure 2 that `Tech`

[11] The IS in some years also has a question about product innovations and whether these product innovations had a technological component. When we compare the conditional means, we find a similar statistically significant difference between firm-year observations with no product innovations (on average lower `Tech`) and those with technological product innovations (on average higher `Tech`), but the number of missing values for this question is so high that we chose not to include this analysis here.

[12] http://ec.europa.eu/eurostat/statistics-explained/index.php/Glossary:High-tech_classification_of_manufacturing_industries.

[13] For this exercise, we use the absolute value of `Tech` because the classification variable here is an importance variable at the industry-level, so we would expect both large positive and large negative values of `Tech` to be found in medium-high to high technology industries with a higher frequency. In practice, since large negative values of `Tech` are rare, the results hold up had we used just plain `Tech`.

had a marked drop in the years after 2000 compared to the last decade of the previous millennium. Table 6 confirms this visual impression, and also shows that the fraction of total investment that goes into restructuring and rationalization activities from the IS as well as the growth rate of annual R&D spending in the German manufacturing sector, which we obtain from the Federal Statistical office, experienced a similar decline.[14]

In sum, the evidence in Tables 2 to 6 taken together, at least suggests that `Tech` captures indeed the effect of technological innovation factors on firm capital expenditures.

`Finance` We next turn to `Finance`. From 1989 through 2001, the spring questionnaire of the IS featured a question about the share of capital expenditures funded by external finance in the preceding year. The basic idea is that `Finance` (in absolute value) should be more important as an investment determinant in firms that rely more on external finance. Indeed, as Table 7 shows, the weighted mean of the absolute value of `Finance` increases monotonically the more firms rely on external finance for their capital expenditures. For example, firms with an external finance share of less than 33.33% on average, the vast majority of firms, respond that financial factors had a 0.25 influence on capital expenditures (given the absolute value, on a scale between zero and two). On the other hand, firms with more than 66.66% of investment financed through external funds state that financial factors had a 0.53 influence on their investment activity. The differences in conditional means between any two terciles are statistically significant at the 1% level, except for the difference between external finance dependence from 33.33% to 66.66% and external finance dependence above 66.66%, which is statistically significant at the 10% level.

In Figure 4 we compare, now in the time series dimension, `Finance` and two other covariate candidates. The top panel shows the yearly average of the monthly series of credit spreads for non-financial corporations from Gilchrist and Mojon (2016). Since this data is only available from 1999 onwards, we approximate, for the time before 1999, credit spreads as

[14] We could not obtain any data for R&D spending separately for the West German manufacturing sector after 1992.

the difference between corporate bond yields, obtained from the Bundesbank, and 10-year German treasuries.[15] Although corporate bonds are only a minor source of external finance in Germany, their yields are a good proxy for bank loans of different sizes and maturities, which are the major source of external finance for German firms.[16] The correlation between `Finance` and credit spreads has the expected negative sign: -0.35.

Similarly, the lower panel compares `Finance` with a measure of idiosyncratic uncertainty in the West German manufacturing sector, the yearly average of the standard deviation of ex-post forecast errors from Bachmann et al. (2013). As Gilchrist et al. (2014) argue, uncertainty shocks can interact with financial frictions so as to cause an increase in the cost of capital followed by a decline in capital expenditures.[17] The correlation between the uncertainty measure and `Finance`, -0.38, is consistent with this view: both panels together show that when idiosyncratic business uncertainty is up (post-reunification and the early 2000 slump), so are the credit spreads. Taken together, the evidence presented in Table 7 and Figure 4 at least suggests that the effect of finance on capital expenditures is captured by `Finance`.

`Sales` Figure 5 compares `Sales` with various time series of general economic activity in the German manufacturing sector (revenues and industrial production), and a proxy for aggregate demand for this sector more specifically (new orders). In particular, the upper-left panel of Figure 5 plots `Sales` and the cyclical component of the volume index of revenues in

[15] The maturity of the corporate bonds yield data does not match exactly with that of 10-year treasuries, as they include all "bonds with agreed maximum maturities of over four years if their mean residual maturities exceed three years", according to the Bundesbank. Nevertheless, the monthly and yearly correlation between our proxy and the credit spreads data by Gilchrist and Mojon (2016) is about 0.90 from 1999 onwards, when we can compare both time series. We thank Gilchrist and Mojon (2016) for providing us with their data.

[16] There does not appear to exist a good longitudinally consistent time series of bank loan interest rates for Germany. The interest rate statistics about euro-denominated loans to non-financial corporations which are resident in the euro area are available from the Bundesbank since 2003. These include loan rates for outstanding amounts and new business, up to 1 million Euro and over 1 million Euro, of German banks with maturity up to one year, between one and five years, or over five years. For the time before 2003, the European Central Bank provides data on national retail interest rates of German banks, broken down by short-term loans to enterprises and medium and long-term loans to enterprises. The correlation between corporate bond yields and the different lending rates is almost always above 0.80 for those periods where we have an overlap in the data.

[17] Other examples of papers that study the link between investment activity and uncertainty through financial frictions are Christiano et al. (2014); Arellano et al. (2012); Chugh (2012); Dorofeenko et al. (2008).

the German manufacturing sector, obtained from the Federal Statistical Office. The cyclical component is extracted by means of the HP-filter with a smoothing parameter of $\lambda = 6.25$ for annual data, following Ravn and Uhlig (2002). The correlation between both time series is positive and high: 0.72. The lower-left panel of Figure 5 displays real production in the German manufacturing sector, obtained from the Federal Statistical Office, at business cycle frequencies ($\lambda = 6.25$). Again, the correlation with `Sales` is positive and high: 0.71. Finally, in the upper-right panel of Figure 5, we plot the HP-filtered ($\lambda = 6.25$) index of new orders in the German manufacturing sector from the Federal Statistical Office. The correlation with the investment determinant index `Sales` is 0.70. Especially the last piece of evidence is consistent with the view that the aggregate investment determinant index `Sales` captures the effect of aggregate demand on capital expenditures in the manufacturing sector.

`Macro` Figure 6 shows the time series of `Macro` and potential fiscal policy covariate candidates. The relation between `Macro` and corporate tax policy is shown in the top panel. Since the firms in the IS are predominantly incorporated entities, which are under corporate tax law, as opposed to single-ownership firms and partnerships, which are subject to personal income taxation, we use the (linearly detrended) corporate tax rate. Its correlation with `Macro` is small: -0.16. The lower panel plots `Macro` and a measure of real government purchases at business-cycle frequencies, that is, HP(6.25)-filtered. Government purchases are defined as the sum of intermediate inputs, wage costs, benefits in kind, and gross investment, obtained from German national accounting (*Volkswirtschaftliche Gesamtrechnung, VGR*) data on expenditures in the government sector. The correlation between the two series is essentially zero: -0.03.

Figure 7 shows the time series of `Macro` and two additional covariate candidates. The top panel displays the linearly detrended monetary policy rate. Until 1998 the discount rate set by the Bundesbank was the principal monetary policy instrument, followed by the main refinancing operations rate set by the European Central Bank. The correlation coefficient

between both series, 0.17, is small and has an unexpected sign.[18] Increases in the monetary policy rate should depress economic activity through higher refinancing costs, and thus if `Macro` captured the monetary policy environment, we should expect a negative correlation with the monetary policy rate.[19]

In contrast, the lower panel shows that `Macro` follows closely the cyclical component of real GDP, obtained from German VGR data and extracted by an HP-filter with smoothing parameter λ = 6.25. The correlation between the two series is 0.50. Taken together, the evidence in Figure 6 and Figure 7 suggests that the aggregate investment determinant index `Macro` does not capture fiscal or monetary policy per se, but rather appears to express firms' assessment of the general macroeconomic environment.

3 Empirical Setup

As has been pointed out above, Table 1 shows that some aggregate investment determinant indices are mutually correlated. In order to extract economically meaningful shocks from these investment determinant indices, we must first orthogonalize them using plausible identification assumptions. Then we calculate the contribution of these orthogonal shocks to aggregate investment growth.

3.1 Identification

We start by assuming that innovations to `Tech`, which we interpret as technology shocks, are orthogonal to innovations in the non-technological investment determinant indices. The economic content of this assumption is that technology within a year is determined by engineering efforts or engineering luck, which themselves are not the result of anything happening

[18] Perhaps the more precise statement is that there seems to be an unstable connection between the monetary policy rate and `Macro`: the post-reunification recession features the expected behavior, that is, monetary policy is tight and `Macro` has a negative influence on manufacturing investment, but afterwards `Macro` and the monetary policy rate comove positively.

[19] The correlation between the monetary policy rate and the investment growth rate, ΔI_t^{FSO}, is essentially zero: -0.08; or slightly negative: -0.24 for ΔI_t^{IFO}.

inside the economic and political sphere in that year. We also implicitly assume that the non-technological investment determinants indeed capture the economic and/or political sphere, and that survey respondents make the same distinction. These relatively mild assumptions are sufficient to estimate the relative contributions of technological and non-technological shocks to aggregate investment dynamics.

In order to identify orthogonal shocks within the group of non-technological investment determinant indices, one has to make more and stronger assumptions. The analysis in Sections 2.3 and 2.4 shows that (i) `Profit` is very highly correlated with `Sales` and does not seem to capture any own, that is, a cost element; (ii) `Macro` captures the general macroeconomic environment, and, in addition, there is little prima facie statistical evidence that it is an important investment determinant, either on average or cyclically; and (iii) `Other` appears to be an (unimportant) residual category. Therefore we orthogonalize these three investment determinant indices with respect to `Technology`, `Sales`, and `Finance`.

To decide about the orthogonalization between `Finance` and `Sales` for our baseline specification, we combine (i) the results from our analysis in Section 2.3, which show that `Finance` is unlikely to be a major aggregate investment determinant on average, has low volatility, and for more than half of the firms in any given year it has no influence on their investment decision; and (ii) the additional observation (consistent with the Section 2.3 results) that external finance in Germany plays a very limited role for investment financing. Bundesbank (2012), for instance, reports that on average about two thirds of total corporate financing in Germany between 1991 and 2010 were raised through internal funds. This observation, in turn, is consistent with the facts about external financing in the IS, as displayed in Table 7, which shows that the vast majority of firm-year observations in the IS have an external finance share for their capital expenditures of less than one third. Therefore, we orthogonalize `Finance` with respect to `Sales` in the baseline specification. As an alternative we also consider a specification where `Sales` is orthogonalized with respect to `Finance` to gauge – loosely speaking – the maximally possible contribution of `Finance` to aggregate investment fluctuations, after conditioning on `Tech`.

Econometrically, the baseline recursive orthogonalization of the aggregate investment determinant indices can be cast into the following regression equations:

$$\texttt{Tech}_t = \nu_1 + \widehat{\texttt{Tech}}_t \tag{3}$$

$$\texttt{Sales}_t = \nu_2 + \delta_{21}\,\widehat{\texttt{Tech}}_t + \widehat{\texttt{Sales}}_t \tag{4}$$

$$\texttt{Finance}_t = \nu_3 + \delta_{31}\,\widehat{\texttt{Tech}}_t + \delta_{32}\,\widehat{\texttt{Sales}}_t + \widehat{\texttt{Finance}}_t \tag{5}$$

$$\texttt{Profit}_t = \nu_4 + \delta_{41}\,\widehat{\texttt{Tech}}_t + \delta_{42}\,\widehat{\texttt{Sales}}_t + \delta_{43}\,\widehat{\texttt{Finance}}_t + \widehat{\texttt{Profit}}_t \tag{6}$$

$$\texttt{Macro}_t = \nu_5 + \delta_{51}\,\widehat{\texttt{Tech}}_t + \delta_{52}\,\widehat{\texttt{Sales}}_t + \delta_{53}\,\widehat{\texttt{Finance}}_t + \delta_{54}\,\widehat{\texttt{Profit}}_t + \widehat{\texttt{Macro}}_t \tag{7}$$

$$\texttt{Other}_t = \nu_6 + \delta_{61}\,\widehat{\texttt{Tech}}_t + \delta_{62}\,\widehat{\texttt{Sales}}_t + \delta_{63}\,\widehat{\texttt{Finance}}_t + \delta_{64}\,\widehat{\texttt{Profit}}_t + \delta_{65}\,\widehat{\texttt{Macro}}_t + \widehat{\texttt{Other}}_t \tag{8}$$

That is, we start by regressing the aggregate investment determinant index `Tech` on a constant. The residual of this regression, $\widehat{\texttt{Tech}}$, is the orthogonal investment determinant index of technology, our measure of technology shocks. We then regress `Sales` on a constant and $\widehat{\texttt{Tech}}$ to obtain the component of `Sales` that is orthogonal to $\widehat{\texttt{Tech}}$, i.e., $\widehat{\texttt{Sales}}$, our measure of aggregate demand shocks. Proceeding recursively in this manner generates the mutually orthogonal innovations to the investment determinant indices, denoted by hat-variables.

In Figure 8 we check for serial correlation in the orthogonalized investment determinant indices. Economically meaningful shocks should not be serially correlated, and, indeed, the serial correlation in the orthogonalized investment determinant indices is not significantly different from zero at the 95 percent level.

3.2 R^2 Decomposition

In order to measure the relative contributions of the orthogonalized shocks to aggregate investment growth, we then estimate the following equation by ordinary least squares:[20]

[20] Figure 9 shows that the residuals of this regression are serially uncorrelated. Given the small number of observations in the time dimension we therefore prefer a static specification without lags of investment growth as our baseline approach (see Section 4.1.8 for a robustness check).

$$\Delta I_t^{FSO} = c + \beta_1 \widehat{\texttt{Tech}_t} + \beta_2 \widehat{\texttt{Sales}_t} + \beta_3 \widehat{\texttt{Finance}_t} + \beta_4 \widehat{\texttt{Profit}_t} + \beta_5 \widehat{\texttt{Macro}_t} + \beta_6 \widehat{\texttt{Other}_t} + u_t \quad (9)$$

where ΔI_t^{FSO} denotes aggregate investment growth from the Federal Statistical Office and c is a constant.

While the magnitude of the β−coefficients in Equation 9 has little economic meaning, we can interpret their signs and their statistical significance (or lack thereof). Also, we can compute the contribution of the six regressors to the fluctuations in aggregate investment growth. To this end, we exploit the fact that the regressors are mutually orthogonal, and therefore the R^2 of this multivariate regression equals the sum of the R^2 of univariate regressions of ΔI_t^{FSO} on each of the orthogonalized aggregate investment determinant indices. This means, we can compute the contribution of every such orthogonalized variable to the overall R^2.

4 Results

4.1 Aggregate Results

4.1.1 The Core Result

The first column of Table 8 shows the results from estimating Equation (9) with ordinary least squares under the baseline orthogonalization (3) - (8) (the second column of the table shows the results when the order of $\widehat{\texttt{Sales}}$ and $\widehat{\texttt{Finance}}$ is flipped). The overall R^2 of the regression is 0.84 in both specifications, which means that more than eighty percent of the total variation in aggregate investment growth is explained by the investment determinants from the IS. This is an important result in its own right: the six orthogonal aggregate shocks identified from the survey explain a very sizeable fraction of aggregate manufacturing investment growth variability documented in administrative statistics.

In the baseline orthogonalization, $\widehat{\texttt{Tech}}$ and $\widehat{\texttt{Sales}}$ affect the aggregate investment growth rate positively, and in a statistically significant way. None of the other determinants matter. This suggests that $\widehat{\texttt{Tech}}$ and $\widehat{\texttt{Sales}}$ explain the bulk of the fluctuations in aggregate investment growth. In the alternative, more finance-friendly orthogonalization $\widehat{\texttt{Finance}}$ has a significant effect, while $\widehat{\texttt{Tech}}$ and $\widehat{\texttt{Sales}}$ continue to remain important and statistically significant.

Building on the variance decomposition outlined in Section 3.2, Table 9 reports the relative contributions of the orthogonalized aggregate investment determinant indices to the overall R^2 of 0.84. Column 1 of Panel A documents the results for the baseline orthogonalization, which assumes that `Tech` is predetermined with respect to shocks in the non-technological investment determinant indices. Aggregate technology shocks account for a significant fraction, 30.19%, of fluctuations in aggregate investment growth. Without imposing more assumptions on the empirical model, the remainder is explained by the non-technological shocks, $\widehat{\texttt{Non-Tech}}$. Columns 2-6 of Panel A in Table 9 display the relative contribution of $\widehat{\texttt{Tech}}$ to the R^2 as `Tech` moves gradually to the last position in the orthogonalization scheme.[21] The contribution of $\widehat{\texttt{Tech}}$ decreases from roughly 30 percent to essentially zero. The 30 percent are thus likely to be an upper bound for the fraction of aggregate investment growth dynamics that is explained by technology shocks.

Imposing the additional identification assumptions for the non-technological aggregate investment determinant indices outlined and motivated in Section 3.1, we can determine the relative contributions of these non-technological shocks to short-run fluctuations in aggregate investment growth. Column 1 of Panel B in Table 9 reports their relative contribution to the R^2 of Equation (9) in the baseline orthogonalization. Of course, the fraction of fluctuations in aggregate investment growth explained by $\widehat{\texttt{Tech}}$ is unaffected when more structure

[21] By construction, the total R^2 in Equation (9) remains unaltered as we go through the different orthogonalization schemes in Tables 8 and 9, because these different orthogonalization schemes correspond to different linear combinations of the aggregate investment determinant indices but leave the overall informational content of the explanatory variables unchanged. Similarly, if the relative position of an investment determinant index in the orthogonalization scheme stays the same, the contribution to aggregate investment growth of its orthogonalized version is unaffected.

is imposed on the non-technological investment determinants. However, the bulk of the variation in aggregate investment growth can now be attributed to $\widehat{\texttt{Sales}}$, which we interpret as representing aggregate demand shocks, which account for 53.89% of the total R^2 and the nature of which we discuss in more detail in Section 4.1.5 below. Financial shocks captured by $\widehat{\texttt{Finance}}$ have a negligible contribution. Given the above discussed nature of firm financing in Germany, we view this as the most plausible interpretation of the evidence. But even in the alternative specification, which is more favorable to financial shocks being a driving force of aggregate investment dynamics, their contribution would only amount to 23.89%, and aggregate demand shocks, $\widehat{\texttt{Sales}}$, would still account for the bulk (33.73%) of aggregate investment fluctuations, as the second column in Table 10 shows. The contributions of $\widehat{\texttt{Profit}}$, $\widehat{\texttt{Macro}}$, and $\widehat{\texttt{Other}}$ to the R^2 are small, as suggested by their statistically insignificant coefficient estimates reported in Table 8.

Finally, the results reported in this section are robust to using real aggregate investment growth on the left-hand side of Equation (9).[22] We use the deflator for gross fixed capital formation in the manufacturing sector, obtained from German VGR data, to calculate growth rates of real investment, and then re-estimate the empirical model. The R^2 of Equation (9) even increases slightly to about 0.89. In addition, qualitatively as well as quantitatively, the relative R^2-contributions of the orthogonalized investment determinants to the overall R^2 of the regression remain unchanged, as Table 11 documents.

4.1.2 Counterfactual Simulations

A slightly different perspective on our results can be obtained from computing counterfactual aggregate investment growth rate series, where we subtract, one at a time, the contribution of one of the orthogonalized investment determinant indices from the fitted investment growth rate series from Equation (9). Figure 10 does so for the baseline orthogonalization scheme. It

[22] Given that the survey asks about nominal investment expenditures at the firm-level, and, presumably, their determinants, we used, as a first pass, nominal investment expenditures also for the aggregate. It is reassuring, however, that our results are essentially unchanged with deflating.

also shows the actual investment growth rate series from the Federal Statistical Office together with the fitted investment growth rate series from Equation (9). Leaving out $\widehat{\texttt{Tech}}$ dampens the "Tech"-boom in the second half of the 1990s, and it misses the slump in the early 2000s. The latter is very much consistent with the view of Germany being the "sick man of Europe" at the time, when Germany's economy was viewed as plagued with structural problems and a lack of innovativeness and dynamism. In addition, just as for the Great Recession, Figure 3 reveals how technology influences investment in a negative way during this slump, namely, as a – in this case more prolonged – relative unimportance of technological determinants for investment: the modal response in this category flips from `Tech` being "weakly positive" to "no influence" during the early 2000s.

Next, $\widehat{\texttt{Sales}}$, i.e., aggregate demand shocks in our interpretation, was important for the post-reunification recession in the early 1990s, and the recovery from the slump in the early 2000s. While for the former episode the negative demand shock is likely attributable to tight monetary policy (see Figure 7), monetary policy was if anything tightening again in the latter episode; also, as Figure 7 shows, `Macro` was not a particularly important investment determinant at the time. For this episode another interpretation of the aggregate demand shock is necessary (see Section 4.1.5 below). Finally, the elimination of $\widehat{\texttt{Finance}}$ hardly changes the fitted investment growth rate series.

4.1.3 Technology News Shocks and Adjustment Costs

In addition to their instantaneous effect on investment, technology shocks may have dynamic effects on capital expenditures. In the presence of adjustment costs, lagged values of technology affect aggregate capital expenditures in the current period. Similarly, with news about its future level, technology one year ahead would have an impact on investment in the current period. Omitting past and future technology shocks from the regression equation thus may underestimate their contribution to investment dynamics. Therefore, we re-estimate the baseline regression with the first lead and lag (one at a time) of $\widehat{\texttt{Tech}}$.

The results of this regression are reported in Table 12. The first column of Table 12 shows that future technology shocks do not significantly influence capital expenditures in the present. Similarly, the coefficient estimate on the first lag of technology shocks in the second column of Table 12 is not statistically significant. There thus seems to be little evidence that the omission of leads and lags of technology shocks from the baseline regression leads us to underestimate the effect of technology shocks on investment dynamics.

4.1.4 Inter-Industry Shock Effects

Thus far, we have implicitly assumed that the shocks we identify are aggregate shocks, and that industry-specific shocks "average out". However, because of input-output linkages between firms of different industries, survey respondents from different industries may have different perceptions of such industry-specific shocks. Industry-specific shocks of one kind may spill over and lead to aggregate fluctuations perceived as another kind. To be concrete, suppose there is a technology shock that is idiosyncratic to industry i, the firms of which might now want to invest and produce more and thus need more inputs from other industries j, so that these industries would experience an increase in their demand-related investment determinant: in particular, if industry i had a small investment share in aggregate manufacturing investment but bought large amounts of inputs from other industries, we might erroneously classify an industry-specific technology shock as an aggregate demand shock (a *downstream channel*).

There might also be another effect, an *upstream channel*: suppose firms from industry i make an invention that is sold to other industries j. This would show up for industry i as a demand-related investment determinant, while it would be a technology-related one for industries j. In particular, if industry i had a large investment share in aggregate manufacturing investment, we might erroneously classify an industry-specific (and investment-specific) technology shock as an aggregate demand shock.

Using input-output tables from the Federal Statistical Office, we can test whether these

inter-industry shock effects are likely to be quantitatively important.[23] To evaluate the first channel, we compute the shares of goods which 2-digit manufacturing industry i buys from every other 2-digit manufacturing industry j, λ_i^j, normalize them to sum to unity, and define a downstream index for industry i, DSI_t^i, as the trade-share-weighted demand shocks of every other industry j:[24]

$$\mathrm{DSI}_t^i = \sum_{j \neq i} \lambda_i^j \, \widehat{\texttt{Sales}}_{jt}, \tag{10}$$

where $\widehat{\texttt{Sales}}_{jt}$ are the investment determinants for industry j, orthogonalized to $\widehat{\texttt{Tech}}_{jt}$.[25] Similarly, to evaluate the second channel, we define the following upstream index for industry i, USI_t^i:

$$\mathrm{USI}_t^i = \sum_{j \neq i} \mu_i^j \, \widehat{\texttt{Tech}}_{jt}, \tag{11}$$

where $\widehat{\texttt{Tech}}_{jt}$ are the technology shocks for industry j, and μ_i^j the shares of goods which 2-digit manufacturing industry i sells to every other 2-digit manufacturing industry j, normalized to sum to unity.

Table 13 reports the coefficients of regressions of, respectively, DSI_t^i on $\widehat{\texttt{Tech}}_{it}$ (in panel A), and USI_t^i on $\widehat{\texttt{Sales}}_{it}$ (in panel B), their standard errors, and the corresponding R^2. The significance level of the coefficients and the R^2 of these regressions are generally low: for the downstream channel, in four out of eight industries the R^2 is below 10 percent, and the maximum R^2 is 22.5 percent in the 'Wood, Paper Printing'-industry. For the upstream channel, it is five out of eight industries that show an R^2 below 10 percent, and the maximum R^2 is 27.6 percent, again in the 'Wood, Paper Printing'-industry.[26] In particular, we find little evidence of inter-industry shock effects for the largest manufacturing subsector 'Machines,

[23] We have these input-output linkage data for the years 1995, 2000, and 2005. Since the variation of these shares over time is small, we take the average intermediate output shares over the three years.

[24] We drop 'Mining' because the number of observations per cross-section in the IS is small for this sector.

[25] $\widehat{\texttt{Tech}}_{jt}$ and $\widehat{\texttt{Sales}}_{jt}$ are the result of the same econometric procedure that has been outlined in Section 3, but run on data from each 2-digit manufacturing industry individually.

[26] For the downstream channel to be important through 'Wood, Paper Printing', this industry would have to have an important contribution of technology shocks to its investment fluctuations, which is not the case, as we will show in Section 4.2 below. To be important through the upstream channel, this industry would have to be large, but its fraction in manufacturing investment is only just over 8 percent (see Table 13).

Cars, and Other Heavy Manufacturing', which has an investment share of just over 45 percent.[27] In sum, there is little evidence that original technology shocks in one small industry get misclassified as (essentially aggregate) demand shocks in the rest of the manufacturing industries; there is also little evidence that original technology shocks in one large industry get misclassified as aggregate demand shocks, because the industries that would correctly classify the investment determinant as technology-related are just too small.

4.1.5 What are the Aggregate Demand Shocks?

Since aggregate demand shocks seem to play a substantial role for at least regular year-to-year fluctuations in aggregate investment growth, we next examine somewhat more closely where they might come from. For instance, do they capture confidence/sentiment, or rather macroeconomic policy? Figure 11 plots $\widehat{\texttt{Sales}}$ from the baseline orthogonalization scheme and three proxy series for confidence: the aggregate business situation index for the West German manufacturing sector from the Ifo Business Cycle Survey[28] (IFO-BS), which captures the current business situation of respondents, the aggregate business expectations index for the West German manufacturing sector (IFO-BE), which summarizes forward-looking questions in the Ifo Business Cycle Survey, and the GfK Consumer Confidence Index (GFK-CC). We use the yearly average of the monthly confidence series. Figure 11 shows that the correlation of $\widehat{\texttt{Sales}}$ from the baseline specification with IFO-BS, IFO-BE, and GFK-CC is fairly strong: 0.78, 0.52, and 0.58, respectively. Especially IFO-BS is highly correlated with our identified aggregate demand shocks.

Of course, innovations in confidence can also reflect news about the future, in particular future technology, in addition to pure sentiments (see Barsky and Sims (2012)). Figure 12 depicts the sample cross-correlations between our identified aggregate technology shocks, $\widehat{\texttt{Tech}}$, from the baseline specification, contemporaneous and at five leads and lags, with IFO-

[27] The lack of an upstream channel for this particular machine-producing industry also suggests that, more specifically, investment-specific technology shocks may not play an important role for investment fluctuations.

[28] A sister survey to the IS that the Ifo conducts.

BS, IFO-BE, and GFK-CC. While all three confidence indicators are positively correlated with $\widehat{\texttt{Tech}}$, so that they might pick up some information about technology as well, none of them is significantly cross-correlated with $\widehat{\texttt{Tech}}$ in a statistical sense. This suggests that, for the most part, our year-to-year aggregate demand shocks capture pure sentiment. This is consistent with the work by Angeletos et al. (2015), which also find that shocks to sentiment can account for a sizable fraction of aggregate investment and output fluctuations.

Macropolicy shocks are another conceivable driver of $\widehat{\texttt{Sales}}$. Figure 13 therefore plots $\widehat{\texttt{Sales}}$ from the baseline specification together with those policy variables for fiscal and monetary policy with which we compared the `Macro` index (see the discussion in Section 2.4 above, and, in particular, Figures 6 and 7). If our aggregate demand shocks were mostly driven by policy shocks, we would expect that they are strongly negatively (positively) correlated with the corporate tax rate or the monetary policy rate (government purchases). However, Figure 13 shows that two of the three pairwise correlation coefficients between $\widehat{\texttt{Sales}}$ and the policy variables have an unexpected sign. The correlation between the corporate tax rate and demand shocks is very weakly positive, while the correlation with government purchases is mildly negative, pointing to countercyclical expenditure policy rather than fiscal policy being a driver of the business cycle. Only the correlation with the monetary policy rate is weakly negative: -0.29, as expected. This sign, however, is mostly driven by one particular episode, the post-reunification recession, which was induced by a contractionary monetary policy shock. While $\widehat{\texttt{Sales}}$ and thus by extension aggregate investment fluctuations seem to be mostly driven by sentiment in terms of regular year-to-year fluctuations, the post-reunification recession is likely an example where the monetary policy shock was the originator (see the discussion above in Section 4.1.2), which is picked up by a large negative impact of $\widehat{\texttt{Sales}}$, which, in turn, lets aggregate investment and sentiment collapse.

4.1.6 The Great Recession: Extended Sample Results

Thus far, we have carried out our baseline analysis on the sample from 1989 to 2008. That is, we excluded the Great Recession, in order to focus on the more regular year-to-year sources of aggregate investment fluctuations. This section presents results when we redo our analysis on the whole sample we have data available, i.e., from 1989 to 2010. To preface our findings, we note that some of the baseline results do change in important ways. At first glance, this may appear as a drawback of our analysis and as an undesirable instability of our results. We view these results, however, as illuminating because the large shock of the Great Recession combined with the narrative evidence from the investment determinants in the survey gives us identification power for this episode, but it also means that caution should be exercised when large and unique events are used to identify more regular business cycle fluctuations. Our premise and claim in this paper is that the narrative survey evidence helps us on both rather distinct fronts.

Table 14 shows the relative contributions of the orthogonal shocks to the R^2 for aggregate investment growth based on the extended sample. The total R^2 remains essentially unchanged: 0.84. In comparison to Table 10, technology shocks now account for about 51 percent of explained investment fluctuations, while the relative contribution of $\widehat{\texttt{Sales}}$ decreases to approximately 42 percent. The relative contributions of the other shocks are largely unchanged. The reason why technology shocks have now become more important for aggregate investment fluctuations in Germany is the finding from Section 2.3: in the Great Recession, the survey responses flip from a majority saying that `Tech` is "weakly positive" to a majority saying that `Tech` has "no influence." Viewed through the lens of the survey and our empirical strategy, the Great Recession in Germany constituted in part a negative technology shock in the sense of a slowing or temporary absence of technological progress for the typical firm, at least as far as its investment activities are concerned. This may perhaps be a somewhat surprising result, but we reiterate that the survey shows that `Tech` captures what it is supposed to capture (see Section 2.4 above), and that our empirical strategy ren-

ders otherwise results for the post-reunification business cycle in Germany that are consistent with the established historical narrative.

Figure 14 repeats the counterfactual exercises where we turn off, each in turn, $\widehat{\texttt{Tech}}$, $\widehat{\texttt{Sales}}$, $\widehat{\texttt{Finance}}$, now on the extended sample. In 2009, aggregate investment growth in the data plummeted by approximately 22 percent while the fitted value of the empirical model predicts a fall of roughly 18 percent. Leaving out the contribution of $\widehat{\texttt{Tech}}$ (the upper left panel in Figure 14), the counterfactual aggregate investment growth rate is only about -2 percent, which means that the unusual absence of technological reasons to invest accounts for most of the decline of manufacturing investment in the Great Recession. Leaving out the contribution of $\widehat{\texttt{Sales}}$ in that year, the counterfactual aggregate investment growth rate is approximately -13 percent, which means that aggregate demand shocks still account for a significant fraction of the decline of aggregate investment during the Great Recession.[29] The narrative for the earlier episodes – $\widehat{\texttt{Sales}}$ being important for the post-reunification recession and the recovery from the slump in the early 2000s, while $\widehat{\texttt{Tech}}$ being the main driver of this slump and the "Tech"-boom prior to it – does not change after the reestimation on the extended sample.

4.1.7 Effects on Industrial Production

In this section, we investigate whether our identified aggregate shocks, estimated from investment-related data, can also explain output fluctuations. To this end, we regress industrial production growth in the West German manufacturing sector on the identified shocks from the baseline orthogonalization and compute again the relative R^2-contributions as described in Section 3.2.

Table 15 shows the results of this analysis. The total R^2 is approximately 0.69, which means that also a sizeable fraction of output fluctuations can be explained by our aggregate shocks that were identified from investment reasons. The bulk of the fluctuations in industrial

[29] We also note that Figure 11 shows a rather strong decline in confidence leading up to the Great Recession; see Burda and Hunt (2011) for a similar observation.

production can again be attributed to aggregate demand shocks, which contribute more than 73 percent (48 percent for the sample that includes the Great Recession) to the overall R^2, while the contribution of technology shocks to output growth fluctuations is 3 percent (23 percent for the extended sample).

4.1.8 An Alternative Empirical Strategy: a VAR

In the baseline empirical specification, Equation 9, we ignored both lags in the left-hand side variable investment growth and dynamics in investment determinants. This has two advantages: first, we can do a clean R^2-decomposition for the orthogonalized investment determinants; second, the lag of serial correlation in both the orthogonalized investment determinants and the residuals of the regression equation 9 justified this parsimonious approach given the relatively short time series in our data. The obvious alternative would have been to use a vector autoregressive (VAR) framework as in, e.g., Romer and Romer (2004), which also puts narratively identified shocks in VARs. VARs are designed to model dynamic interactions between variables as well as serial correlation in them. One of the disadvantages of VARs, however, is their highly parameterized nature: if we wanted to estimate a VAR with one lag that included aggregate investment growth and all six investment determinants, we would have to estimate 84 parameters.

However, with the results from the previous sections in mind that aggregate investment growth ist mostly determined by two factors, `Tech`, `Sales`, we can employ a lower-parameterized VAR in these two determinants plus ΔI_t^{IFO} to provide additional support for our baseline results. We also note that a VAR is an alternative to address the concern we have discussed in Section 4.1.3 in the context of technology shocks, namely, that lagged shocks may influence current investment growth because of, e.g., investment adjustment costs.

Formally, let $F_t = (\texttt{Tech}_t, \texttt{Sales}_t)$. The joint dynamics of F_t and the aggregate investment growth rate, ΔI_t^{FSO}, are governed by the following VAR with one lag:

$$\begin{bmatrix} F_t \\ \Delta I_t^{FSO} \end{bmatrix} = \nu + \Phi \begin{bmatrix} F_{t-1} \\ \Delta I_{t-1} \end{bmatrix} + \epsilon_t, \tag{12}$$

where ν is a 3×1 vector of constants and Φ is a coefficient matrix. We identify the structural shocks, which are linear combinations of the reduced-form innovations ϵ_t, via a standard recursive identification, which extends our identifying assumptions outlined in Section 3.1 to the dynamic context.

Figure 15 plots the Impulse Response Functions (IRFs) of each variable in response to technology shocks, aggregate demand shocks, and a residual shock. For statistical inference, we compute the "bootstrap-after-bootstrap" 95% confidence interval proposed by Kilian (1998). The solid blue lines show the impulse responses based on the ordinary least squares (OLS) point estimate. The bottom row of Figure 15 depicts the IRFs of interest: a positive, but mild, and not persistent effect of technology on aggregate investment growth, a strongly positive and persistent effect of aggregate demand on aggregate investment growth, and a small unexplained effect from the residual shock. Reassuringly, neither the technology index nor the sales index react to the residual shock at any horizon (on impact this is by construction), which means that the aggregate investment determinant indices are not confounded by other unexplained shocks.

Table 16 displays the forecast error variance decomposition at the five-year horizon[30] for each variable and shock, both for the baseline and the extended samples. As the first and the second row show, fluctuations in `Tech` and `Sales` are almost fully accounted for by technology shocks and aggregate demand shocks, respectively. The bottom row of Table 16 shows that the bulk of investment dynamics is accounted for by demand shocks, approximately 72 percent, while technology shocks contribute approximately 14 percent to aggregate investment fluctuations. As in the baseline empirical framework, the importance of technology shocks

[30] Given the yearly frequency and the small serial correlation present in the IRFs, the five-year horizon forecast error variance decomposition corresponds essentially to the long-run, i.e., the unconditional variance of each variable.

increases somewhat when the Great Recession is included (to 23 percent), and demand shocks have a somewhat lower contribution (63 percent). Qualitatively and, by and large, quantitatively, the relative contributions of technology and demand shocks to aggregate investment dynamics in the VAR framework are very similar to the results from the regression in the baseline specification.[31]

Finally, the historical decomposition in Figure 16 confirms the narrative from our counterfactual exercises in Sections 4.1.2 and 4.1.6: the post-reunification recession was caused by a (monetary policy induced) demand shock, investment was positively influenced by technological factors during the worldwide "Tech"-boom in the second half of the 1990s, and negatively influenced by the same factors during the slump in the early 2000s; the short boom afterwards was demand-driven, in our interpretation: driven by positive sentiments, and the Great Recession was a combination of a negative technology shock and a negative demand shock.

4.2 Semi-Aggregate Results

Thus far, and with one exception in Section 4.1.4, our analysis has focused on the West-German manufacturing aggregate and common shocks that affect all manufacturing industries. In this section, we use semi-aggregate specifications at the two-digit industry level, and at the German state, the Laender level, to uncover potential heterogeneities in the driving forces of investment fluctuations. Using the weights defined in Section 2.2, we first compute IS investment determinant indices by two-digit industry and by Land. We have eight industries:[32] Chemical Industry, Oil; Plastics, Rubber; Glass, Ceramics; Metals; Machinery; Wood, Paper, Printing; Textiles, Leather; Food, Tobacco. For the regional split we use eight

[31]Indeed, the correlation between the structural shocks from the VAR and the orthogonal investment determinant indices in the baseline specification is close to unity: 0.80 in the case of technology shocks, and 0.96 in the case of demand shocks.

[32]The Ifo Investment Survey records the four-digit WZ03 and WZ08 industrial classification codes from 2003 and 2008, respectively, used in the German national accounting system. From these we map the firm-level observations into two-digit industries. We drop data for the 'Mining' sector because the number of observations in the cross-section of this industry is small in the IS.

out of the eleven West German Laender: Baden-Württemberg, Bavaria, Hamburg, Hesse, Lower Saxony, North Rhine-Westphalia, Rhineland-Palatinate, and Schleswig-Holstein.[33]

We compute the orthogonal semi-aggregate shocks by applying the recursive orthogonalization procedure described in Section 3.1 for each industry/Land. To estimate the relative contribution of each such orthogonal shock to the corresponding investment growth rate, we use the industry-level and regional equivalents of Equation (9), separately for each industry and Land. The left-hand-side investment growth rates by industry are for West Germany until 1991, but from 1992 they are for Germany as a whole (a finer split is not available at the 2-digit level); the Laender investment growth rates are only available since 1992 and as total (not just manufacturing) investment growth rates, which means we have a slightly shorter sample period.

Figure 17 displays box-plots of the estimates for the relative contributions of orthogonal shocks to the overall R^2 at the two-digit industry level for the baseline orthogonalization. The rightmost box-plot depicts the overall R^2 of the industry-level regressions. While the explanatory power of the investment determinant indices constructed from the IS slightly decreases at the semi-aggregate level, the R^2 still remains above two third in most of the industries. The median of the R^2 across all industries is 0.73.

The leftmost box-plot of Figure 17 shows the relative contributions of $\widehat{\texttt{Tech}}_i$ to the industry-level investment growth rates. Although it is well below 20% for four out of the eight industries, in two industries $\widehat{\texttt{Tech}}_i$ accounts for more than 30% of the short-run fluctuations in capital expenditure growth: 32% in 'Coal, Chemicals, and Petroleum', and 35% in 'Machines, Cars, and Other Heavy Manufacturing'. By and large, these industry-level results confirm the aggregate evidence from Section 4.1 that technology is important for investment fluctuations, but not its most important driver. This is also visually confirmed in Figure 18, where we plot the counterfactual investment growth rate by 2-digit industry, leaving out the contributions of $\widehat{\texttt{Tech}}_i$, against the fitted and actual investment growth rates for the same

[33] We drop data from Bremen, Saarland and West Berlin because cross-sections from these Laender in the IS are small, just as the Laender themselves.

industry. The counterfactual investment growth rate is usually very close to the fitted one.

Also, the finding that $\widehat{\texttt{Sales}}$ explains most of the short-run fluctuations in investment largely carries over to the industry level. The second box-plot of Figure 17 displays the contribution of $\widehat{\texttt{Sales}}_i$ to the overall R^2. The industry-level median estimate is approximately 63.5%, and the range goes from 45% in 'Coal, Chemicals, and Petroleum' to 89% in 'Food, Tobacco'. The R^2-contributions of the other orthogonalized investment determinants are small. Altogether, the result that most industries behave like the aggregate combined with the lack of evidence for strong inter-industry shock effects (see Section 4.1.4) suggests that our aggregate baseline specification is a good empirical approach and that aggregate shocks account for the bulk of aggregate investment fluctuations.

The Laender results are shown in Figure 19, the counterfactual results without $\widehat{\texttt{Tech}}_i$ in Figure 20. The median overall R^2 across all Laender is 0.60. The relative contributions of $\widehat{\texttt{Tech}}_i$ to regional investment growth do not exceed 10 percent in any Land. The results for the non-technological regional investment determinant indices are qualitatively and, to a large extent, quantitatively similar to the results for the aggregate and the industry-level. With the exception of two small outliers, Schleswig-Holstein and Hamburg, the contribution of $\widehat{\texttt{Sales}}_i$ to the overall R^2 is larger than 50 percent.

In sum, the semi-aggregate evidence presented in this subsection lends support to the finding from aggregate data that aggregate technology shocks are a significant, but not the major contributor to short-run investment dynamics. Instead, the largest part of investment fluctuations is explained by demand shocks, while financial shocks seem to play only a minor role, if any, in the German investment cycle. Tables 17 and 18 summarize these findings by displaying the investment-weighted relative R^2-contributions across, respectively, all eight manufacturing 2-digit industries and eight West German Laender. Our disaggregate results, which, to a large extent, replicate the aggregate findings on many time series, also alleviate somewhat the concern that these aggregate results might be spurious because they are estimated from a relatively short time series.

5 Conclusion

This paper uses a novel yet complementary-to-the-literature approach to address an important problem in macroeconomics: the sources of aggregate fluctuations, here investment fluctuations. We use survey data from the Ifo Investment Survey about subjective investment determinants to uncover what drives the dynamics of investment in the West German manufacturing sector. Consistent with neoclassical views of the economy, we find that, on average, technology is the most important investment determinant. Regular year-to-year fluctuations, however, are best explained by aggregate demand shocks that appear to be related to business and consumer sentiment.

The historical narrative reveals nevertheless a complex and rich picture: while monetary policy seems unimportant for investment fluctuations for most of the sample period, the post-reunification recession demand shock we find is likely a monetary policy shock. The "Tech"-boom in the late 1990s and the extended slump at the beginning of the 2000s – Germany being the "sick man of Europe" – can be attributed to a high/low importance of technological considerations, while the boom afterwards looks like a positive sentiment shock. Perhaps surprisingly, the investment slump in the Great Recession has signs of a technological slow down in addition to being the result of a negative demand shock, and the survey data show its anatomy: negative technology shocks are a retardation of technological progress.

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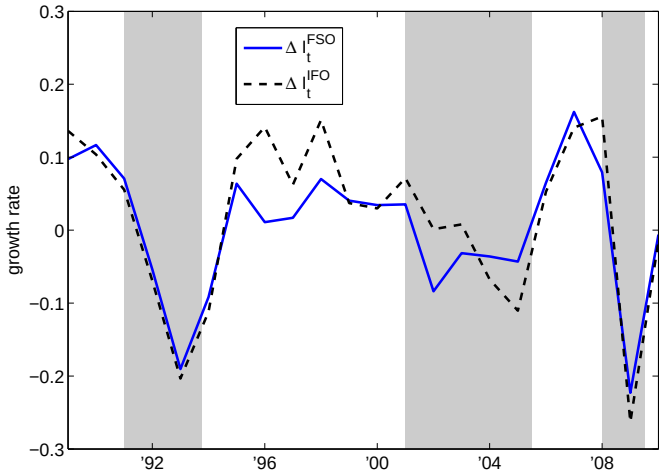
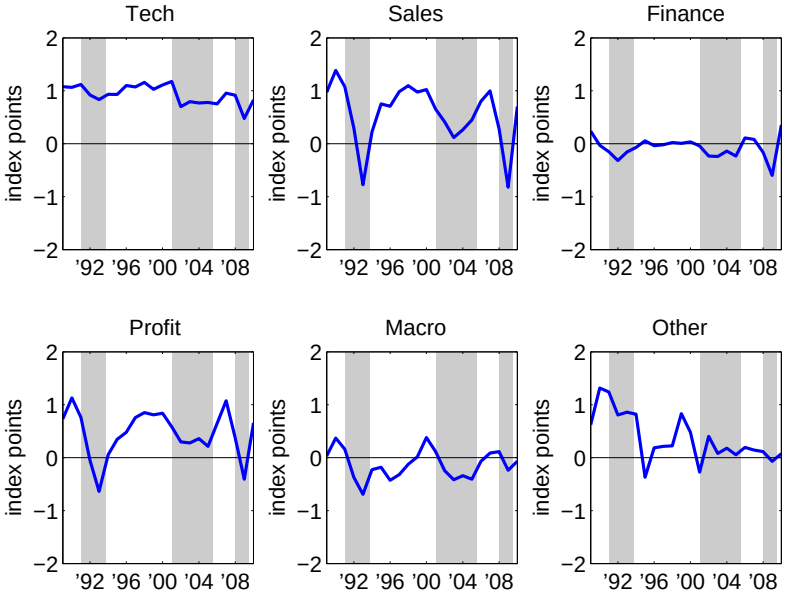
Figure 1 – Measures of Aggregate Investment Growth ($\rho = 0.91$)



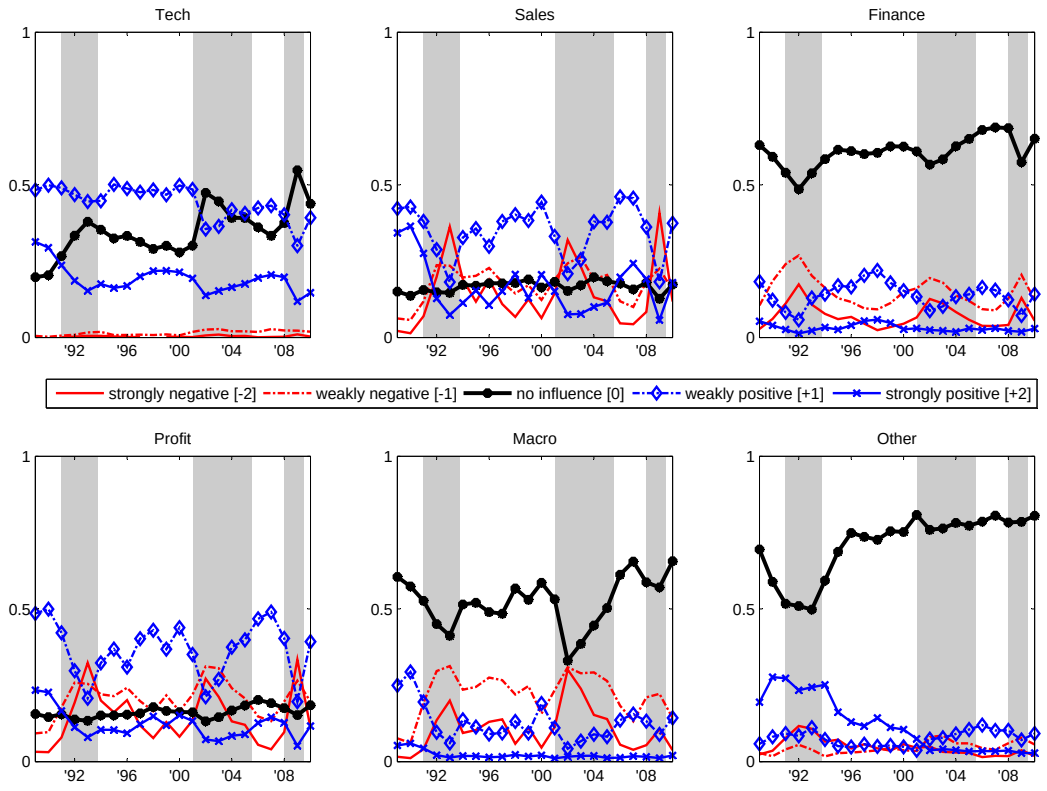
Notes: This figure plots two measures of the aggregate investment growth rate in the West German manufacturing sector. ΔI_t^{FSO} is administrative data and obtained from the Federal Statistical Office. ΔI_t^{IFO} is the growth rate implied by the Ifo Investment Survey, obtained from aggregating the firm-level responses to **Q1** with weights as described in the text. The correlation coefficient between ΔI_t^{FSO} and ΔI_t^{IFO}, ρ, is 0.91. The sample period goes from 1989 to 2010. The gray-shaded regions show recessions as dated by the Sachverständigenrat (see Sachverständigenrat, 2009, p. 261): I/1991 - III/1993, I/2001 - II/2005, I/2008 - II/2009.

Figure 2 – Aggregate Investment Determinant Indices



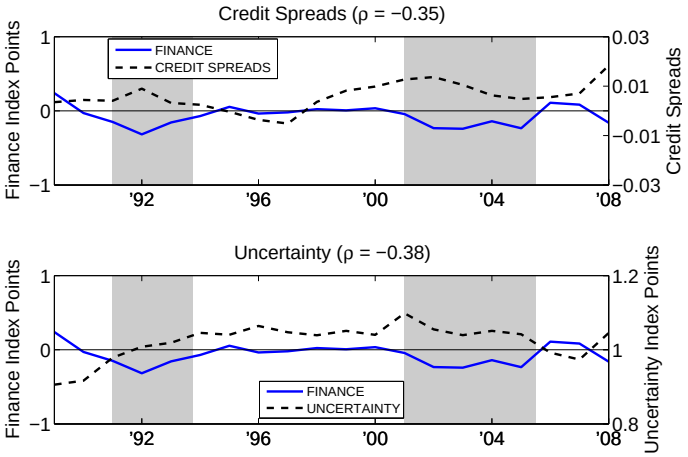
Notes: The panels show the aggregate investment determinant indices `Tech`, `Finance`, `Sales`, `Profit`, `Macro`, and `Other` for the West German manufacturing sector, constructed from aggregating the firm-level responses to **Q2** with weights as described in the text. Index values above zero represent a positive and index values below zero a negative effect on investment activity. The sample period goes from 1989 to 2010. The gray-shaded regions show recessions as dated by the Sachverständigenrat (see Sachverständigenrat, 2009, p. 261): I/1991 - III/1993, I/2001 - II/2005, I/2008 - II/2009.

Figure 3 – Fraction of Survey Respondents in Each Answer Category



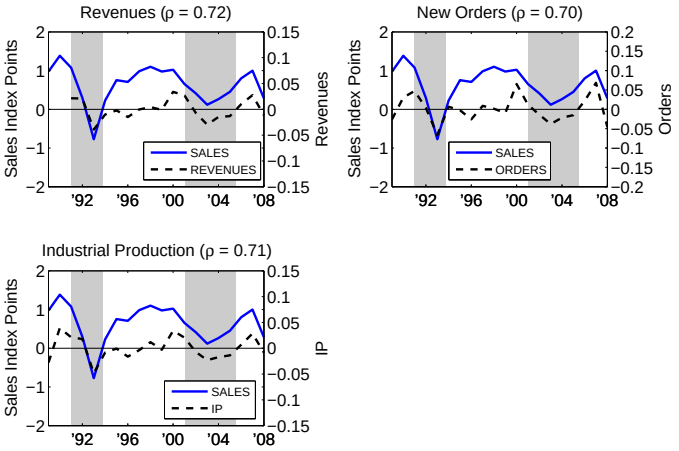
Notes: Each panel of this graph shows the fraction of survey respondents per answer category – "strongly negative", "weakly negative", "no influence", "weakly positive", or "strongly positive" – for each of the six investment determinants: `Tech`, `Sales`, `Finance`, `Profit`, `Macro`, and `Other` for the West German manufacturing sector. The sample period goes from 1989 to 2010. The gray-shaded regions show recessions as dated by the Sachverständigenrat (see Sachverständigenrat, 2009, p. 261): I/1991 - III/1993, I/2001 - II/2005, I/2008 - II/2009.

Figure 4 – Investment Determinant Index `Finance`, Credit Spreads and Idiosyncratic Firm Uncertainty



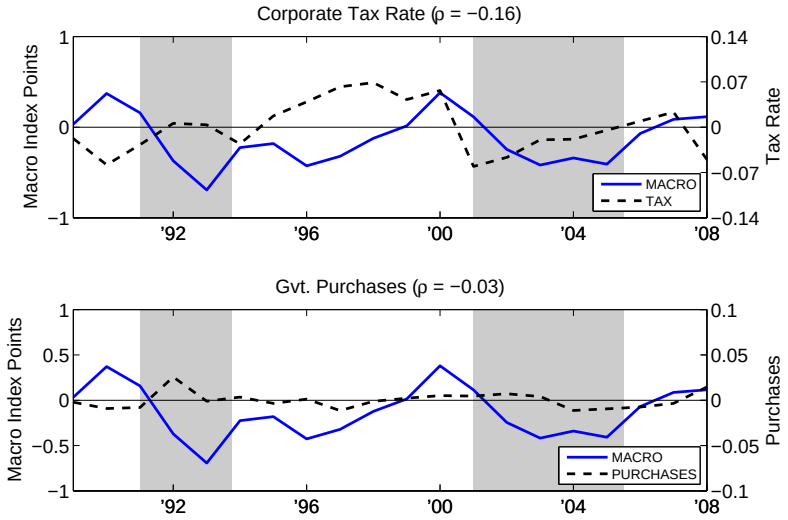
Notes: This figure compares the aggregate investment determinant index `Finance`, based on **Q2**, and two covariate candidates. The top panel plots `Finance` and credit spreads for non-financial corporations. From 1999 onwards, *CREDIT SPREADS* is the yearly average of monthly credit spreads for non-financial corporations from Gilchrist and Mojon (2016). For the time before 1999, *CREDIT SPREADS* is the difference between corporate bond yields, obtained from the Bundesbank, and interest rates on 10-year Treasuries. The bottom-panel compares `Finance` and a measure of idiosyncratic uncertainty in the West German manufacturing sector. *UNCERTAINTY* is the yearly average of the standard deviation of ex-post forecast errors from Bachmann et al. (2013). The panel titles report the correlation coefficient between the two time series shown, ρ. The sample period goes from 1989 to 2008. The gray-shaded regions show recessions as dated by the Sachverständigenrat (see Sachverständigenrat, 2009, p. 261): I/1991 - III/1993 and I/2001 - II/2005.

Figure 5 – Investment Determinant Index `Sales`, Aggregate Revenues, New Orders and Industrial Production



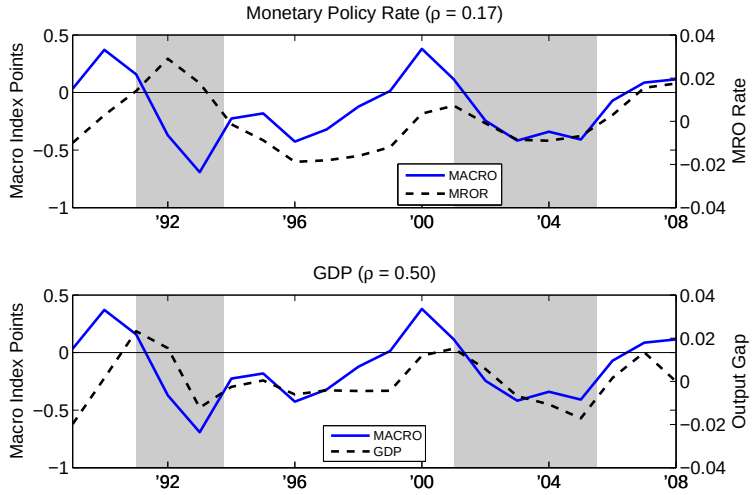
Notes: The top-left panel displays the aggregate investment determinant index `Sales`, based on **Q2**, and revenues. *REVENUES* is the cyclical component of the volume index of revenues in the German manufacturing sector, obtained from the Federal Statistical Office and extracted via the HP-filter ($\lambda = 6.25$) after taking logs. The top-right panel compares `Sales` and new orders. *ORDERS* is the HP-filtered ($\lambda = 6.25$) series of the log of real new orders in the German manufacturing sector, taken from the Federal Statistical Office. The bottom-left panel depicts `Sales` and industrial production. *IP* is the volume index of industrial production in the German manufacturing sector at business cycle frequencies, obtained from the Federal Statistical Office and extracted via the HP-filter ($\lambda = 6.25$) after taking logs. The panel titles report the correlation coefficient between the two time series shown, ρ. The sample period goes from 1989 to 2008. *REVENUES* is only available since 1991. The gray-shaded regions show recessions as dated by the Sachverständigenrat (see Sachverständigenrat, 2009, p. 261): I/1991 - III/1993 and I/2001 - II/2005.

Figure 6 – Investment Determinant Index `Macro` and Fiscal Policy Covariate Candidates



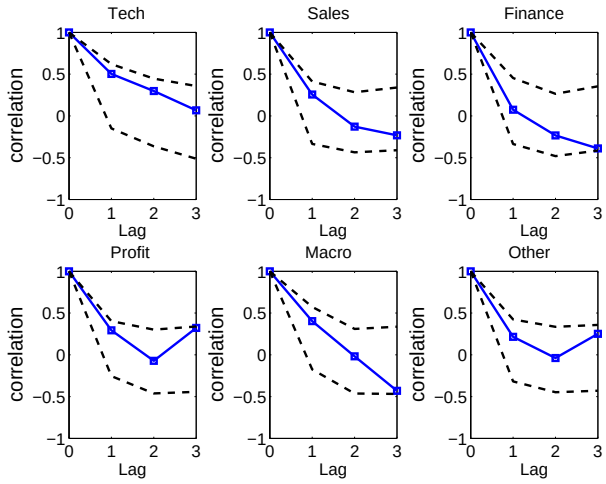
Notes: The top panel compares the aggregate investment determinant index `Macro`, based on **Q2**, and *TAX*, which is the linearly detrended corporate tax rate obtained from the Organization for Economic Co-operation and Development. The lower panel depicts `Macro` and government purchases. *PURCHASES* is the cyclical component of real government purchases (intermediate inputs, wage costs, benefits in kind, and gross investment) from German VGR (*Volkswirtschaftliche Gesamtrechnung*) data and filtered by means of the HP-filter (λ = 6.25) after taking logs. The panel titles report the correlation coefficient between the two time series shown, ρ. The sample period goes from 1989 to 2008. The gray-shaded regions show recessions as dated by the Sachverständigenrat (see Sachverständigenrat, 2009, p. 261): I/1991 - III/1993 and I/2001 - II/2005.

Figure 7 – Investment Determinant Index `Macro` and Other Covariate Candidates



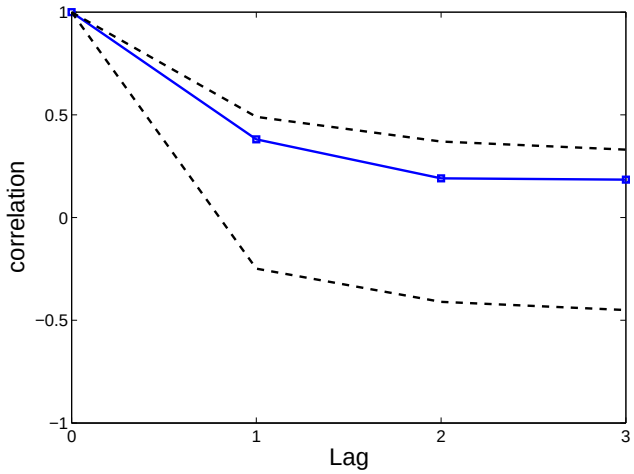
Notes: The top panel compares the aggregate investment determinant index `Macro`, based on **Q2**, and the monetary policy rate. *MROR* (Main Refinancing Operations Rate) is the discount rate set by the Bundesbank until 1998, followed by the main refinancing operations rate set by the European Central Bank since 1999, jointly adjusted for a linear trend. The bottom panel compares `Macro` and the cyclical component of real gross domestic product, taken from German VGR (*Volkswirtschaftliche Gesamtrechnung*) data and extracted via the HP-filter (λ = 6.25) after taking logs. The panel titles report the correlation coefficient between the two time series shown, ρ. The sample period goes from 1989 to 2008. The gray-shaded regions show recessions as dated by the Sachverständigenrat (see Sachverständigenrat, 2009, p. 261): I/1991 - III/1993 and I/2001 - II/2005.

Figure 8 – Serial Correlation of Orthogonalized Investment Determinants in the Baseline Specification.



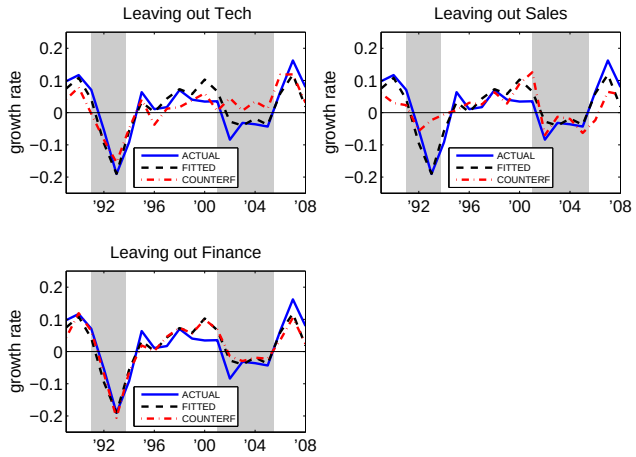
Notes: The panels display the serial correlation, contemporaneous and at three lags, of the orthogonalized aggregate investment determinant indices, $\widehat{\texttt{Tech}}$, $\widehat{\texttt{Sales}}$, $\widehat{\texttt{Finance}}$, $\widehat{\texttt{Profit}}$, $\widehat{\texttt{Macro}}$, and $\widehat{\texttt{Other}}$. The investment determinant indices are based on **Q2** and the orthogonal shocks are recovered as described in the text. The recursive orthogonalization scheme is: `Tech`, `Sales`, `Finance`, `Profit`, `Macro`, `Other`. The dashed lines represent the upper and lower bound of the 95% confidence interval for the correlation coefficient estimate obtained from a moving-block bootstrap with overlapping blocks of 3 years length and 10,000 replications. The sample period goes from 1989 to 2008.

Figure 9 – Serial Correlation of Residuals in the Baseline Specification.



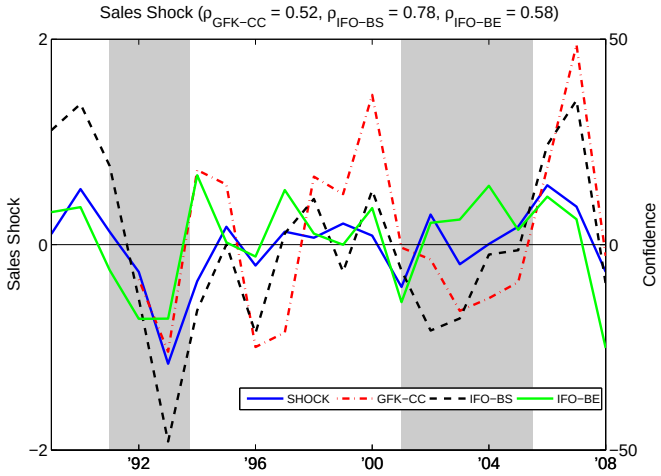
Notes: This figure plots the serial correlation, contemporaneous and at three lags, of the residuals in a regression of aggregate investment growth in the West German manufacturing sector on the orthogonalized aggregate investment determinant indices, that is, Equation 9. The aggregate investment growth rate is obtained from the Federal Statistical Office. The investment determinant indices are based on **Q2** and the orthogonal shocks are recovered as described in the text. The recursive orthogonalization scheme is: `Tech`, `Sales`, `Finance`, `Profit`, `Macro`, `Other`. The dashed lines represent the upper and lower bound of the 95% confidence interval for the correlation coefficient estimate obtained from a moving-block bootstrap with overlapping blocks of 3 years length and 10,000 replications. The sample period goes from 1989 to 2008.

Figure 10 – Fit and Counterfactuals in the Baseline Specification



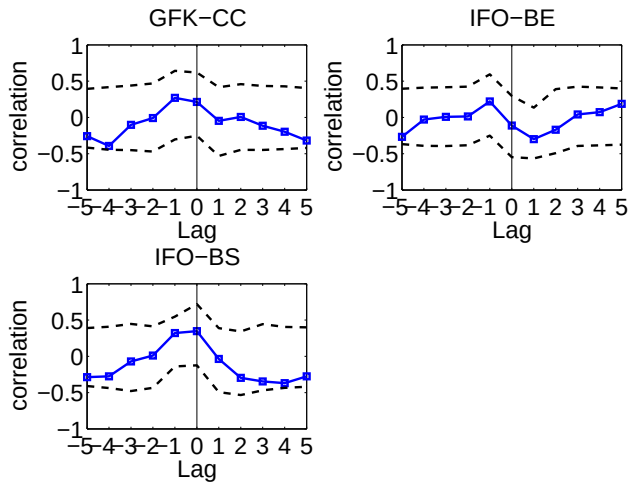
Notes: This figure plots the West German manufacturing investment growth rate obtained from the Federal Statistical Office ($ACTUAL$), the fitted series of the aggregate investment growth rate estimated from Equation (9) ($FITTED$), and, in three different panels, a counterfactual fitted series of the aggregate investment growth rate ($COUNTERF$), where, respectively and separately, the contribution of $\widehat{\texttt{Tech}}$, $\widehat{\texttt{Sales}}$ and $\widehat{\texttt{Finance}}$ to the overall fitted series has been left out. This figure plots the case of the baseline orthogonalization. The sample period goes from 1989 to 2008. The gray-shaded regions show recessions as dated by the Sachverständigenrat (see Sachverständigenrat, 2009, p. 261): I/1991 - III/1993 and I/2001 - II/2005.

Figure 11 – $\widehat{\texttt{Sales}}$ from the Baseline Specification and Confidence Indicators



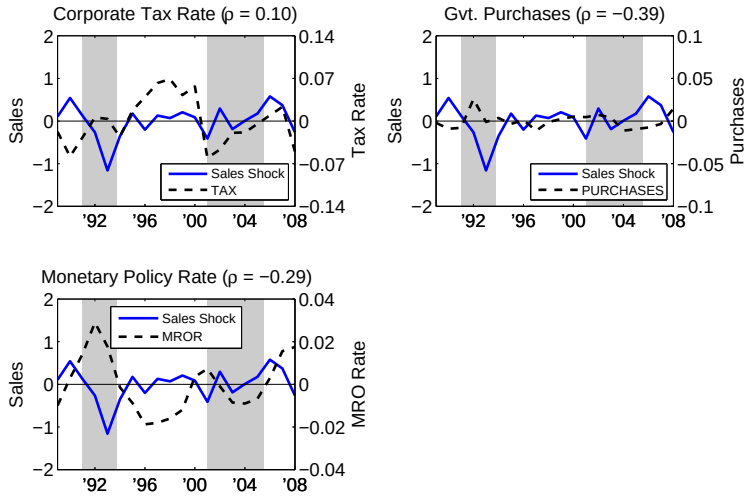
Notes: The figure plots $\widehat{\texttt{Sales}}$ from the baseline specification (left y-axis), along with, on the right y-axis, the GfK Consumer Confidence Index (GFK-CC), the Ifo business situation index for the West German manufacturing sector (IFO-BS), and the Ifo business expectation index (IFO-BE) for the West German manufacturing sector, the latter two from the Ifo Business survey. The sample period goes from 1989 to 2008; the GFK index is only available from 1992. The gray-shaded regions show recessions as dated by the Sachverständigenrat (see Sachverständigenrat, 2009, p. 261): I/1991 - III/1993 and I/2001 - II/2005.

Figure 12 – Dynamic Cross-correlations between $\widehat{\texttt{Tech}}$ from the Baseline Specification and Confidence Indicators



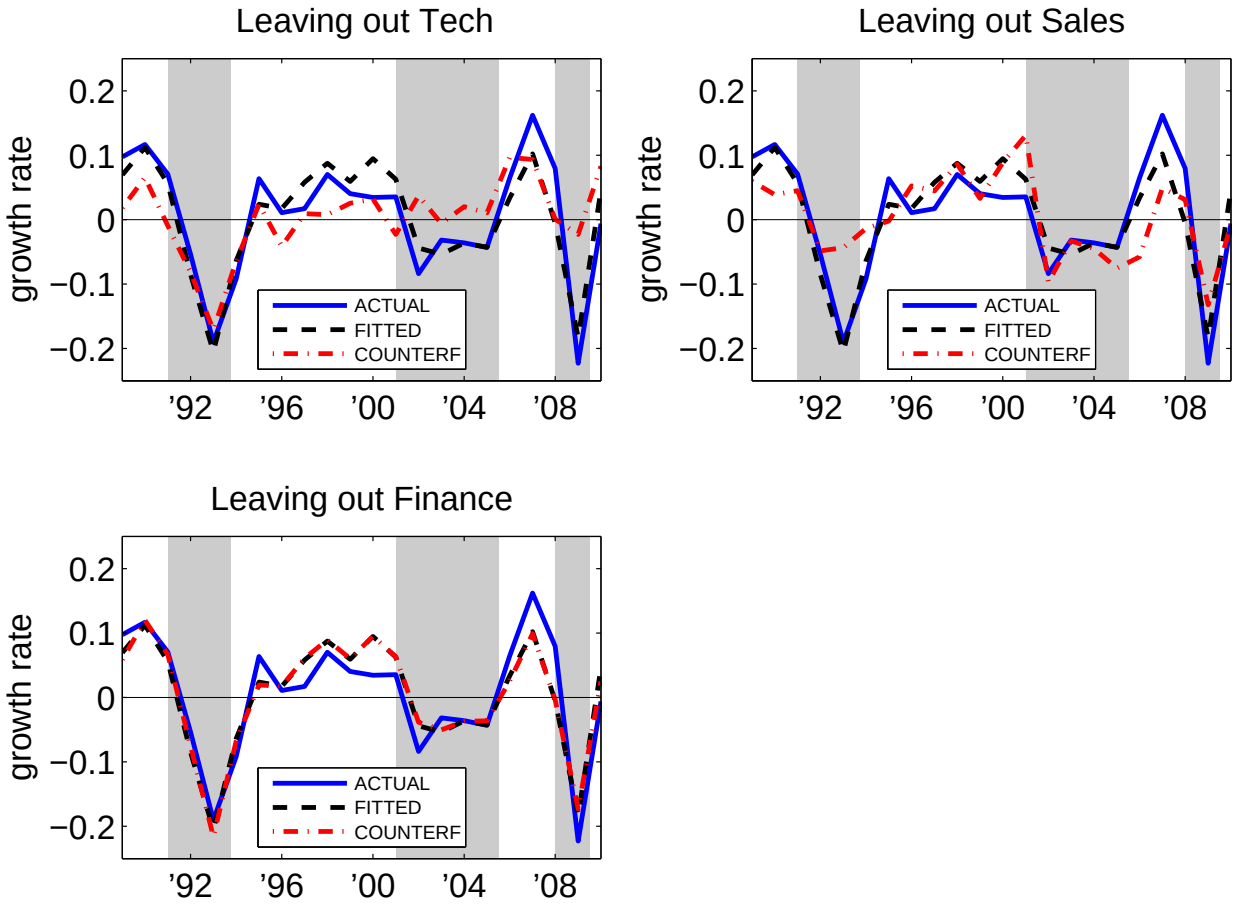
Notes: The figure shows the cross-correlation of $\widehat{\texttt{Tech}}$ from the baseline specification with the GfK Consumer Confidence Index (GFK-CC), the Ifo business situation index for the West German manufacturing sector (IFO-BS), and the Ifo business expectation index (IFO-BE) for the West German manufacturing sector, the latter two from the Ifo Business survey. The dashed lines represent the upper and lower bound of the 95% confidence interval for the correlation coefficient estimate obtained from a moving-block bootstrap with overlapping blocks of 3 years length and 10,000 replications. The sample period goes from 1989 to 2008; the GFK index is only available from 1992.

Figure 13 – $\widehat{\texttt{Sales}}$ from the Baseline Specification and Policy Variables



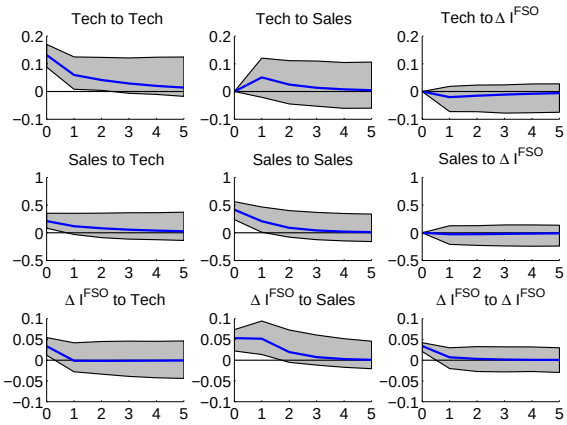
Notes: The figure plots $\widehat{\texttt{Sales}}$ from the baseline specification against policy variables measuring monetary and fiscal policy. The top-left panel shows the linearly detrended corporate tax rate obtained from the Organization for Economic Co-operation and Development. The top-right panel depicts the cyclical component of real government purchases (intermediate inputs, wage costs, benefits in kind, and gross investment) from German VGR (Volkswirtschaftliche Gesamtrechnung) data and filtered with the HP-filter ($\lambda = 6.25$) after taking logs. The bottom panel shows the discount rate set by the Bundesbank until 1998, followed by the main refinancing operations rate set by the European Central Bank since 1999, jointly adjusted for a linear trend. The panel titles report the correlation coefficient between the two time series shown, ρ. The sample period goes from 1989 to 2008. The gray-shaded regions show recessions as dated by the Sachverständigenrat (see Sachverständigenrat, 2009, p. 261): I/1991 - III/1993 and I/2001 - II/2005.

Figure 14 – Fit and Counterfactuals in the Baseline Specification: Extended Sample Results



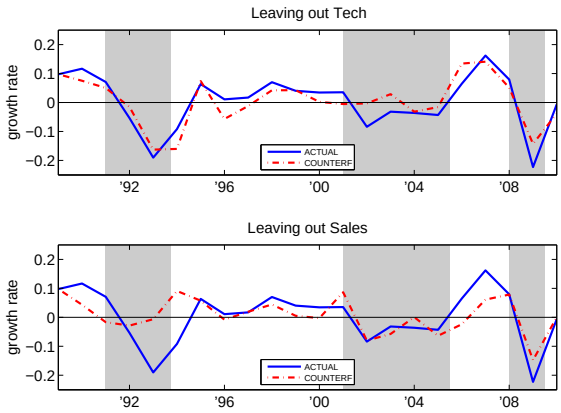
Notes: This figure plots the West German manufacturing investment growth rate obtained from the Federal Statistical Office ($ACTUAL$), the fitted series of the aggregate investment growth rate estimated from Equation (9) ($FITTED$), and, in three different panels, a counterfactual fitted series of the aggregate investment growth rate ($COUNTERF$), where, respectively and separately, the contribution of $\widehat{\texttt{Tech}}$, $\widehat{\texttt{Sales}}$ and $\widehat{\texttt{Finance}}$ to the overall fitted series is eliminated. This figure plots the case of the baseline orthogonalization. The sample period goes from 1989 to 2010. The gray-shaded regions show recessions as dated by the Sachverständigenrat (see Sachverständigenrat, 2009, p. 261): I/1991 - III/1993, I/2001 - II/2005, I/2008 - II/2009..

Figure 15 – Impulse Response Functions of a Vector Autoregression in `Tech`, `Sales`, and ΔI_t^{IFO}



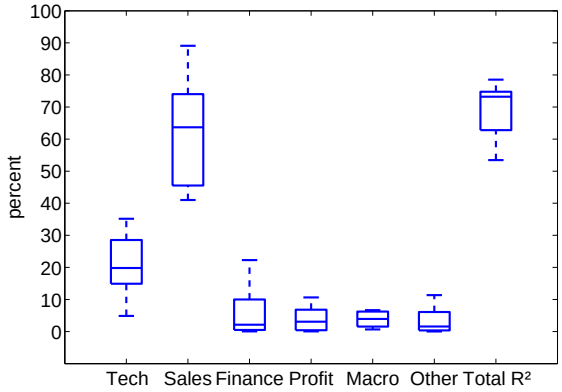
Notes: This figure depicts the impulse response functions of a vector autoregression with one lag in the aggregate investment determinant indices `Tech`, `Sales`, and the aggregate investment growth rate, ΔI_t^{IFO}. Identification of structural shocks is based on the Cholesky decomposition of the variance-covariance matrix of the residuals. The gray-shaded regions show the 95% confidence intervals based on the "bootstrap-after-bootstrap" method by Kilian (1998). The sample period goes from 1989 to 2008.

Figure 16 – Historical Decompositions from a Vector Autoregression in `Tech`, `Sales`, and ΔI_t^{IFO}



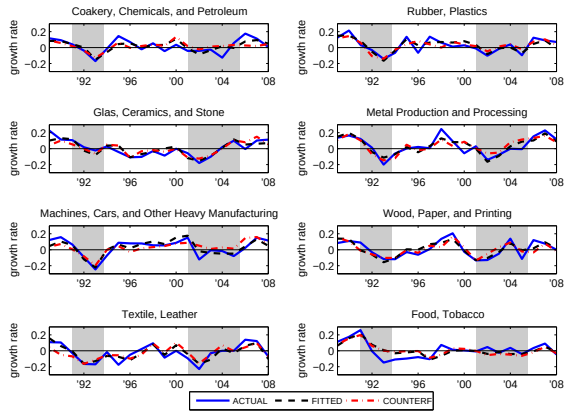
Notes: This figure depicts historical decompositions from a vector autoregression with one lag in the aggregate investment determinant indices `Tech`, `Sales`, and the aggregate investment growth rate, ΔI_t^{IFO}. The upper panel shows the counterfactual path of the aggregate investment growth rate, leaving out the structural technology shocks `Tech`; the lower panel does the same, leaving out the structural demand shocks from `Sales`. Identification of structural shocks is based on the Cholesky decomposition of the variance-covariance matrix of the residuals. The sample period goes from 1989 to 2010.

Figure 17 – Relative Contributions of Orthogonalized Shocks to the R^2 in the Baseline Specification at the Two-Digit Industry Level



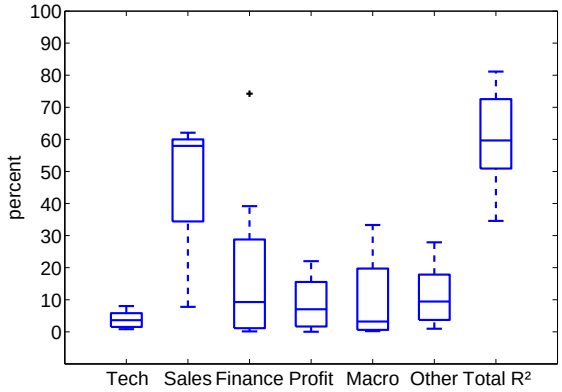
Notes: This figure depicts the box-plots of estimates for the relative contributions of shocks to investment fluctuations at the two-digit manufacturing industry level. The estimates are obtained from a decomposition of the R^2 in regressions of investment growth on the orthogonalized industry investment determinant indices, $\widehat{\texttt{Tech}}_i$, $\widehat{\texttt{Sales}}_i$, $\widehat{\texttt{Finance}}_i$, $\widehat{\texttt{Profit}}_i$, $\widehat{\texttt{Macro}}_i$, and $\widehat{\texttt{Other}}_i$, estimated for eight two-digit industries. The sample period goes from 1989 to 2008. The industry-specific investment growth rates and investment determinant indices are based on German VGR (*Volkswirtschaftliche Gesamtrechnung*) data (for 1989 to 1991 we use West German data, and data for all of Germany thereafter) and **Q2**, respectively. The orthogonal shocks are recovered and the variance decomposition is calculated as described in the text. The recursive orthogonalization scheme is: $\texttt{Tech}_i$, $\texttt{Sales}_i$, $\texttt{Finance}_i$, $\texttt{Profit}_i$, $\texttt{Macro}_i$, $\texttt{Other}_i$. The first six box-plots show the relative contributions of orthogonal shocks to the R^2 by industry. The final box-plot displays the overall R^2. The ends of the whiskers represent the lowest and highest estimates from the lowest and highest quartile, respectively, within 1.5 times the interquartile range.

Figure 18 – Fit and the Leaving Out $\widehat{\texttt{Tech}}_i$ Counterfactual in the Baseline Specification by Two-Digit Industry.



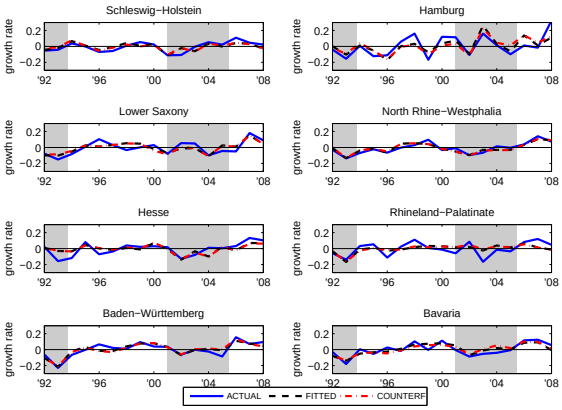
Notes: This figure plots the 2-digit manufacturing investment growth rates obtained from the Federal Statistical Office ($ACTUAL$), the fitted series of the investment growth rate estimated from a 2-digit industry version of Equation (9) ($FITTED$), and counterfactual fitted series of the investment growth rate ($COUNTERF$), where the contribution of $\widehat{\texttt{Tech}}_i$ to the overall fitted series has been left out. This figure plots the case of the baseline orthogonalization. The sample period goes from 1989 to 2008. The gray-shaded regions show recessions as dated by the Sachverständigenrat (see Sachverständigenrat, 2009, p. 261): I/1991 - III/1993 and I/2001 - II/2005.

Figure 19 – Relative Contributions of Orthogonalized Shocks to the R^2 in the Baseline Specification at the Laender Level



Notes: This figure depicts the box-plots of estimates for the relative contributions of shocks to investment fluctuations at the Laender level. The estimates are obtained from a decomposition of the R^2 in regressions of investment growth on the orthogonalized Laender investment determinant indices, $\widehat{\texttt{Tech}}_i$, $\widehat{\texttt{Sales}}_i$, $\widehat{\texttt{Finance}}_i$, $\widehat{\texttt{Profit}}_i$, $\widehat{\texttt{Macro}}_i$, and $\widehat{\texttt{Other}}_i$, estimated for eight West German Laender. The sample period goes from 1992 to 2008. The Laender-specific investment growth rates and investment determinant indices are based on German VGR (*Volkswirtschaftliche Gesamtrechnung*) data (only for aggregate, not for manufacturing investment available) and **Q2**, respectively. The orthogonal shocks are recovered and the variance decomposition is calculated as described in the text. The recursive orthogonalization scheme is: $\texttt{Tech}_i$, $\texttt{Sales}_i$, $\texttt{Finance}_i$, $\texttt{Profit}_i$, $\texttt{Macro}_i$, $\texttt{Other}_i$. The first six box-plots show the relative contributions of orthogonal shocks to the R^2 by Laender. The final box-plot displays the overall R^2. The ends of the whiskers represent the lowest and highest estimates from the lowest and highest quartile, respectively, within 1.5 times the interquartile range. Outliers are plotted as '+'.

Figure 20 – Fit and the Leaving Out $\widehat{\texttt{Tech}}_i$ Counterfactual in the Baseline Specification by German Laender.



Notes: This figure plots the Laender-level investment growth rates obtained from the Federal Statistical Office ($ACTUAL$), the fitted series of the investment growth rate estimated from a Laender version of Equation (9) ($FITTED$), and counterfactual fitted series of the investment growth rate ($COUNTERF$), where the contribution of $\widehat{\texttt{Tech}}_i$ to the overall fitted series has been left out. This figure plots the case of the baseline orthogonalization. The sample period goes from 1992 to 2008. The gray-shaded regions show recessions as dated by the Sachverständigenrat (see Sachverständigenrat, 2009, p. 261): I/1992 - III/1993 and I/2001 - II/2005.

Table 1 – Unconditional Moments of the Aggregate Investment Determinant Indices

	Tech	Sales	Finance	Profit	Macro	Other	ΔI_t^{FSO}
Baseline Sample Results (1989-2008)							
Panel A:							
Tech	1						
Sales	0.6071***	1					
Finance	0.4574**	0.5801***	1				
Profit	0.5434***	0.9434***	0.5920***	1			
Macro	0.5253***	0.7337***	0.4674***	0.7746***	1		
Other	0.1676	0.0879	-0.1100	0.0241	0.2073	1	
Panel B:							
ΔI_t^{FSO}	0.5029***	0.8392***	0.6279***	0.8849***	0.7601***	-0.1073	1
Panel C:							
μ	0.9602	0.6347	-0.0641	0.4947	-0.1275	0.4062	0.0166
σ	0.1490	0.4889	0.1391	0.4173	0.2846	0.4567	0.0832
Extended Sample Results (1989-2010)							
Panel D:							
Tech	1						
Sales	0.7205***	1					
Finance	0.5167***	0.6648***	1				
Profit	0.6299***	0.9475***	0.6493***	1			
Macro	0.4622***	0.6569***	0.3849***	0.7329***	1		
Other	0.2797	0.1871	-0.0111	0.1038	0.2105	1	
Panel E:							
ΔI_t^{FSO}	0.6580***	0.8846***	0.6507***	0.8983***	0.6808***	0.0386	1
Panel F:							
μ	0.9321	0.5716	-0.0695	0.4610	-0.1298	0.3695	0.0047
σ	0.1768	0.5599	0.1982	0.4431	0.2721	0.4509	0.0942

Notes: Panel A reports the pairwise correlation coefficients between the aggregate investment determinant indices, obtained from aggregating the firm-level responses to **Q2** with weights as described in the text. Panel B shows the correlations of the aggregate investment determinant indices with the aggregate investment growth rate in the West German manufacturing sector, ΔI_t^{FSO}, obtained from the Federal Statistical Office. Significance at the 1%, 5%, and 10% level is indicated by ***, **, and * , respectively. The statistical significance levels are based on a moving-block bootstrap with overlapping blocks of 3 years length and 10,000 replications, where we compute the fraction of bootstrap samples for which the correlation coefficient equals zero or has opposite sign of the point estimate. Panel C contains the sample means and the sample standard deviations of the aggregate investment determinant indices and the aggregate investment growth rate. The sample period in Panels A-C goes from 1989 to 2008. Panels D-F show the same statistics as Panels A-C, but for the extended sample period from 1989 to 2010.

Table 2 – Mean of `Tech` Conditional on Maintenance Investment

Tercile	N	Mean(`Tech`)
1	9521	1.048428
2	10765	0.8196647
3	8156	0.7707991

Notes: This table displays the conditional mean of the investment determinant index `Tech`, which is based on **Q2**, across firm-year observations. The mean uses the weights as described in the text and is conditional on the terciles of the fraction of maintenance investment, extracted from the Ifo Investment Survey. The sample period goes from 1989 to 2008. Differences in conditional means between any two terciles are statistically significant at the 1% level, based on a one-sided t test.

Table 3 – Mean of `Tech` Conditional on Investment in Restructuring and Rationalization

Tercile	N	Mean(`Tech`)
1	11341	0.7818501
2	7690	0.9721699
3	9411	1.125008

Notes: This table displays the conditional mean of the investment determinant index `Tech`, which is based on **Q2**, across firm-year observations. The mean uses the weights as described in the text and is conditional on the terciles of the shares of restructuring and rationalization investment as a fraction of total investment for a given firm-year, extracted also from the Ifo Investment Survey. The sample period goes from 1989 to 2008. Differences in conditional means between any two terciles are statistically significant at the 1% level, based on a one-sided t test.

Table 4 – Mean of `Tech` Conditional on Process Innovation

Process Innovation	N	Mean(`Tech`)
No	11653	0.9512173
Yes	5810	1.096788

Notes: This table displays the conditional mean of the investment determinant index `Tech`, which is based on **Q2**, across firm-year observations. The mean uses the weights as described in the text and is conditional on whether capital expenditures for a given firm-year also aimed at process innovation, extracted from the Ifo Investment Survey. The corresponding question was asked in the spring questionnaire for the preceding year from 1989 until the year 2001. Differences in conditional means between Yes and No answers are statistically significant at the 1% level, based on a one-sided t test.

Table 5 – Mean of |`Tech`| Conditional on Eurostat's Technology Classification

Industries	N	Mean(|`Tech`|)
Low-technology	10911	0.8956025
Medium-low-technology	8448	0.9669374
Medium-high/High-technology	8645	0.9783141

Notes: This table displays the conditional mean of the absolute value of the investment determinant index `Tech`, which is based on **Q2**, across firm-year observations. The mean uses the weights as described in the text and is conditional on Eurostat's technology classifications, which groups together manufacturing industries according to their technological intensity, defined as the ratio of industry R&D spending to value added. We lump the Medium-high-technology and High-technology industries together because the latter has only 1144 firm-year observations in the Ifo Investment Survey. The sample period goes from 1989 to 2008. Differences in means between any two technology industries are statistically significant at the 1% level, based on a one-sided t test, except for the difference between Medium-low-technology industries and Medium-high/High-technology industries, which is statistically insignificant.

Table 6 – Conditional Time Series Means of `Tech`

	1989-2000	2001-2010
`Tech`	1.0295	0.8153
RES+RAT Share	41.47%	32.29%
R&D (% GROWTH)	0.0366	0.0199

Notes: This table displays, for two different decades, the time series means of, respectively, `Tech`, the fraction of total investment that goes into restructuring and rationalization activities from the Ifo Investment Survey, and the growth rate of nominal annual R&D spending in the German manufacturing sector from the Federal Statistical office; the latter time series only starts in 1992.

Table 7 – Mean of |`Finance`| Conditional on External Finance Dependence

Share of External Finance	N	Mean(|`Finance`|)
up to 33.33%	11564	0.2520984
33.33% to 66.66%	2194	0.5049183
above 66.66%	1982	0.5344153

Notes: This table displays the conditional mean of the absolute value of the investment determinant index `Finance`, which is based on **Q2**, across firm-year observations. The mean uses the weights as described in the text and is conditional on the share of external finance raised for capital expenditures, extracted also from the Ifo Investment Survey. The corresponding question was asked in the spring questionnaire from 1989 until the year 2001. Differences in conditional means between any two external finance dependence terciles are statistically significant at the 1% level, based on a one-sided t test, except for the difference between external finance dependence from 33.33% to 66.66% and external finance dependence above 66.66%, which is only statistically significant at the 10% level.

Table 8 – Regression Results for the Baseline and the Alternative Specification

Dependent Variable	ΔI_t^{FSO}	

Orthogonalization:	`Tech`
	`Sales`
	`Finance`
	`Profit`
	`Macro`
	`Other`
		`Tech`
		`Finance`
		`Sales`
		`Profit`
		`Macro`
		`Other`

$\widehat{\texttt{Tech}}$	0.2809	0.2809
	(0.0954)	(0.0954)
$\widehat{\texttt{Sales}}$	0.1439	0.1259
	(0.0348)	(0.0401)
$\widehat{\texttt{Finance}}$	0.1316	0.3008
	(0.1450)	(0.1305)
$\widehat{\texttt{Profit}}$	0.1559	0.1559
	(0.1143)	(0.1146)
$\widehat{\texttt{Macro}}$	0.0559	0.0559
	(0.1065)	(0.1066)
$\widehat{\texttt{Other}}$	-0.0309	-0.0309
	(0.0400)	(0.0400)
Constant	0.0166	0.0166
	(0.0181)	(0.0181)
N	20	20
R^2	0.8377	0.8377

Notes: The table shows the results of regressing the aggregate investment growth rate in the West German manufacturing sector on the orthogonalized aggregate investment determinant indices for the baseline and the alternative orthogonalization between `Sales` and `Finance` (Equation 9). The sample period goes from 1989 to 2008. The aggregate investment growth rate is obtained from the Federal Statistical Office and the investment determinant indices are based on **Q2**. The orthogonal shocks are recovered as described in the text. The recursive orthogonalization scheme is shown above each column. Bootstrap estimates of the standard error in parentheses, obtained from a moving-block bootstrap with overlapping blocks of 3 years length and 10,000 replications.

Table 9 – Relative Contributions to the R^2 (in percent) with Different Orthogonalizations of `Tech`

Orthogonalization:	`Tech` `Sales` `Finance` `Profit` `Macro` `Other`	`Sales` `Tech` `Finance` `Profit` `Macro` `Other`	`Sales` `Finance` `Tech` `Profit` `Macro` `Other`	`Sales` `Finance` `Profit` `Tech` `Macro` `Other`	`Sales` `Finance` `Profit` `Macro` `Tech` `Other`	`Sales` `Finance` `Profit` `Macro` `Other` `Tech`
Panel A:						
$\widehat{\texttt{Tech}}$	30.19	0.01	0.16	0.00	0.07	0.01
$\widehat{\texttt{Non-Tech}}$	69.81	99.99	99.84	100.00	99.93	99.99
Panel B:						
$\widehat{\texttt{Sales}}$	53.89	84.07	84.07	84.07	84.07	84.07
$\widehat{\texttt{Finance}}$	3.73	3.73	3.58	3.58	3.58	3.58
$\widehat{\texttt{Profit}}$	7.65	7.65	7.65	7.81	7.81	7.81
$\widehat{\texttt{Macro}}$	1.67	1.67	1.67	1.67	1.60	1.60
$\widehat{\texttt{Other}}$	2.87	2.87	2.87	2.87	2.87	2.93
R^2	0.8377					

Notes: This table reports the relative R^2-contributions of the orthogonal aggregate shocks to aggregate investment growth fluctuations in the West German manufacturing sector. The estimates are obtained from a decomposition of the R^2 in a regression of investment growth on the orthogonal shocks (Equation 9). The sample period goes from 1989 to 2008. The aggregate investment growth rate is obtained from the Federal Statistical Office. The investment determinant indices are based on **Q2**. *Panel A* assumes that `Tech` is predetermined with respect to shocks in the non-technological investment determinant indices. The recursive orthogonalization scheme is shown above each column.

Table 10 – Relative Contribution to the R^2 (in percent)

Orthogonalization:	`Tech` `Sales` `Finance` `Profit` `Macro` `Other`	`Tech` `Finance` `Sales` `Profit` `Macro` `Other`
$\widehat{\texttt{Tech}}$	30.19	30.19
$\widehat{\texttt{Sales}}$	53.89	33.73
$\widehat{\texttt{Finance}}$	3.73	23.89
$\widehat{\texttt{Profit}}$	7.65	
$\widehat{\texttt{Macro}}$	1.67	
$\widehat{\texttt{Other}}$	2.87	
R^2	0.8377	

Notes: This table reports the relative R^2-contributions of the orthogonal aggregate shocks to aggregate investment growth fluctuations in the West German manufacturing sector for the baseline and the alternative orthogonalization between `Sales` and `Finance`. See the notes to Table 9 for further information.

Table 11 – Relative Contribution to the R^2 (in percent) in Deflated Specification

Orthogonalization:	Tech Sales Finance Profit Macro Other
$\widehat{\texttt{Tech}}$	26.74
$\widehat{\texttt{Sales}}$	52.19
$\widehat{\texttt{Finance}}$	4.73
$\widehat{\texttt{Profit}}$	9.58
$\widehat{\texttt{Macro}}$	0.13
$\widehat{\texttt{Other}}$	6.63
R^2	0.8876

Notes: This table reports the relative R^2-contributions of the orthogonal aggregate shocks to real aggregate investment growth fluctuations in the West German manufacturing sector for the baseline orthogonalization between `Sales` and `Finance`. We use the deflator for gross fixed capital formation in the manufacturing sector, obtained from German VGR (*Volkswirtschaftliche Gesamtrechnung*) data to deflate investment numbers. See the notes to Table 9 for further information.

Table 12 – Regression Results for the Baseline Specification with Leads and Lags of $\widehat{\texttt{Tech}}$

Dependent Variable	ΔI_t^{FSO}	
	Lead	Lag
$\widehat{\texttt{Tech}}$	0.3539	0.3238
	(0.1165)	(0.1320)
$\widehat{\texttt{Sales}}$	0.1676	0.1438
	(0.0511)	(0.0531)
$\widehat{\texttt{Finance}}$	0.2081	0.0460
	(0.1912)	(0.2108)
$\widehat{\texttt{Profit}}$	0.0653	0.1374
	(0.1467)	(0.1633)
$\widehat{\texttt{Macro}}$	-0.0102	0.0692
	(0.1280)	(0.1220)
$\widehat{\texttt{Other}}$	-0.0029	-0.0302
	(0.0515)	(0.0500)
Lead/Lag of $\widehat{\texttt{Tech}}$	-0.1181	-0.1063
	(0.1708)	(0.1305)
Constant	0.0095	0.0150
	(0.0252)	(0.0273)
N	19	19
R^2	0.8952	0.8557

Notes: The table reports the results of regressing the aggregate investment growth rate in the West German manufacturing sector on the orthogonalized aggregate investment determinant indices for the baseline specification, including one-year ahead (in the first column) and one-year lagged (in the second column) innovations in technology, $\widehat{\texttt{Tech}}$. See the notes to Table 8 for further information. Bootstrap estimates of the standard error in parentheses, obtained from a moving-block bootstrap with overlapping blocks of 3 years length and 10,000 replications.

Table 13 – Inter-Industry Shock Effects

	Coal, Chemicals, Petroleum	Rubber, Plastics	Glass, Ceramics, Stone	Metal Production and Processing	Machines, Cars, Other Heavy Manufacturing	Wood, Paper, Printing	Textile, Leather	Food, Tobacco
Panel A: Downstream Channel								
β	0.6764	0.7626	0.4405	-0.1414	0.4186	1.1074	0.8202	0.9721
std. error	0.3769	0.5516	0.3491	0.8023	0.4317	0.4846	0.4558	0.6397
R^2	0.1518	0.0960	0.0813	0.0017	0.0496	0.2249	0.1525	0.1137
Panel B: Upstream Channel								
β	0.1026	0.0667	0.0425	0.0986	0.0331	0.1619	0.0481	0.2355
std. error	0.0583	0.1082	0.0551	0.1126	0.0514	0.0461	0.1569	0.1433
R^2	0.1518	0.0272	0.0576	0.0453	0.0230	0.2763	0.0099	0.2331
Share in Percent	13.77	4.67	4.44	12.19	45.15	8.09	1.86	9.83

Notes: For each two-digit manufacturing industry in the Ifo Investment Survey (we leave out 'Mining') panel A of the table reports the regression results for regressions of a downstream index, DSI_t^i, on industry-level technology shocks, $\widehat{\texttt{Tech}}_{it}$. The downstream index is the trade-weighted average of demand shocks in all other two-digit industries, as defined in Equation 10. Panel B of the table reports the regression results for regressions of an upstream index, USI_t^i, on industry-level demand shocks, $\widehat{\texttt{Sales}}_{it}$. The upstream index is the trade-weighted average of technology shocks in all other two-digit industries, as defined in Equation 11. The last row shows the time series average of the nominal investment expenditures per manufacturing subsector as a fraction of total nominal investment expenditures in German manufacturing.

Table 14 – Relative Contribution to the R^2 (in percent): Extended Sample Results

Orthogonalization:	`Tech` `Sales` `Finance` `Profit` `Macro` `Other`
$\widehat{\texttt{Tech}}$	51.43
$\widehat{\texttt{Sales}}$	41.61
$\widehat{\texttt{Finance}}$	0.80
$\widehat{\texttt{Profit}}$	4.45
$\widehat{\texttt{Macro}}$	0.35
$\widehat{\texttt{Other}}$	1.36
R^2	0.8420

Notes: This table reports the relative R^2-contributions of the orthogonal aggregate shocks to aggregate investment growth in the West German manufacturing sector for the baseline orthogonalization between `Sales` and `Finance`. The sample period goes from 1989 to 2010. See the notes to Table 9 for further information.

Table 15 – Relative Contribution to the R^2 with ΔIP_t as Dependent Variable.

Orthogonalization:	Tech Sales Finance Profit Macro Other
Baseline Sample Results	
Panel A:	
$\widehat{\texttt{Tech}}$	3.32
$\widehat{\texttt{Sales}}$	73.30
$\widehat{\texttt{Finance}}$	15.87
$\widehat{\texttt{Profit}}$	4.30
$\widehat{\texttt{Macro}}$	0.01
$\widehat{\texttt{Other}}$	3.19
R^2	0.6880
Extended Sample Results	
Panel B:	
$\widehat{\texttt{Tech}}$	23.02
$\widehat{\texttt{Sales}}$	48.42
$\widehat{\texttt{Finance}}$	27.29
$\widehat{\texttt{Profit}}$	0.00
$\widehat{\texttt{Macro}}$	1.20
$\widehat{\texttt{Other}}$	0.07
R^2	0.7895

Notes: This table reports the relative R^2-contributions of the orthogonal aggregate shocks to aggregate industrial production growth fluctuations in the West German manufacturing sector for the baseline orthogonalization between `Sales` and `Finance`. Panel A contains the baseline sample results for the period from 1989 to 2008. Panel B contains the extended sample results for the period from 1989 to 2010. See the notes to Table 9 for further information.

Table 16 – Five-year Forecast Error Variance Decomposition for a Vector Autoregression in `Tech`, `Sales`, and ΔI_t^{IFO}

	Contribution of		
	Technology Shock	Aggregate Demand Shock	Residual Shock
Baseline Sample Results			
`Tech`	84.69	12.38	2.94
`Sales`	23.18	76.17	0.65
ΔI_t^{IFO}	13.80	71.51	14.70
Extended Sample Results			
`Tech`	71.35	12.45	16.20
`Sales`	28.73	61.92	9.35
ΔI_t^{IFO}	23.10	62.19	14.72

Notes: This table reports the five-year forecast error variance decomposition of a vector autoregression with one lag in the aggregate investment determinant indices `Tech`, `Sales`, and the aggregate investment growth rate, ΔI_t^{IFO}. Identification of structural shocks is based on the Cholesky decomposition of the variance-covariance matrix of the residuals. The baseline sample period goes from 1989 to 2008, the extended sample periods goes from 1989 to 2010.

Table 17 – Weighted Average of Relative Contribution to the R^2 (in percent) at the Two-Digit Industry Level

Orthogonalization:	Tech Sales Finance Profit Macro Other
Baseline Sample Results	
$\widehat{\texttt{Tech}}$	25.99
$\widehat{\texttt{Sales}}$	53.68
$\widehat{\texttt{Finance}}$	5.01
$\widehat{\texttt{Profit}}$	5.27
$\widehat{\texttt{Macro}}$	4.25
$\widehat{\texttt{Other}}$	5.79
Extended Sample Results	
$\widehat{\texttt{Tech}}$	36.12
$\widehat{\texttt{Sales}}$	50.00
$\widehat{\texttt{Finance}}$	4.01
$\widehat{\texttt{Profit}}$	3.54
$\widehat{\texttt{Macro}}$	2.94
$\widehat{\texttt{Other}}$	3.38

Notes: This table reports the investment-weighted average of the relative R^2-contributions of shocks to investment fluctuations at the two-digit manufacturing industry level in the baseline orthogonalization for the baseline sample and the extended sample period. The baseline sample period goes from 1989 to 2008, the extended sample periods goes from 1989 to 2010. See the notes to Figure 17 for further information.

Table 18 – Weighted Average of Relative Contribution to the R^2 (in percent) at the Laender Level

Orthogonalization:	Tech Sales Finance Profit Macro Other
Baseline Sample Results	
$\widehat{\texttt{Tech}}$	3.08
$\widehat{\texttt{Sales}}$	56.78
$\widehat{\texttt{Finance}}$	9.26
$\widehat{\texttt{Profit}}$	7.20
$\widehat{\texttt{Macro}}$	10.78
$\widehat{\texttt{Other}}$	12.90
Extended Sample Results	
$\widehat{\texttt{Tech}}$	7.94
$\widehat{\texttt{Sales}}$	55.06
$\widehat{\texttt{Finance}}$	10.32
$\widehat{\texttt{Profit}}$	7.59
$\widehat{\texttt{Macro}}$	7.62
$\widehat{\texttt{Other}}$	11.47

Notes: This table reports the investment-weighted average of the relative R^2-contributions of shocks to investment fluctuations at the Laender level in the baseline orthogonalization for the baseline sample and the extended sample period. The baseline sample period goes from 1992 to 2008, the extended sample periods goes from 1992 to 2010. See the notes to Figure 19 for further information.

Appendix: Survey Guidelines

The Ifo Investment Survey gives the following guidelines on the firm-level investment determinants to complete **Q2** of the survey questionnaire:

Sales Situation and Expectation To be considered are aspects like the degree of capacity utilization, the expected range of price movements and changes in sales figures, and an assessment of the uncertainty surrounding these expectations.

Finance This counts factors like disposable financial resources, borrowing costs, and interest rate expectations.

Profit Expectation To be considered are factors like the return on investment and the relative attractiveness of fixed assets and financial assets.

Technical Factors This comprises all incentives to invest which come from technical development.

Macro Policy Environment To be considered are aspects such as an assessment of the effects of economic policy, the tax regulations applying to investment, as well as the possibility to outsource production abroad.