Seasonalities in Common Stock Returns
Evidence from Germany and Sweden

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Abstract

This paper studies return seasonalities in the cross-section of German and Swedish listed common stocks. We find that stock returns in both countries exhibit traditional return patterns, such as short-term reversal, momentum, and signs of long-term reversal effects. We observe that current-calendar-month returns are positively correlated with historical same-calendar-month returns. This annual seasonality pattern is visible for up to ten years. However, it varies significantly when constructing different subsamples, based on geography, time periods, or firm characteristics. The annual pattern is stronger for Swedish stocks in general. Trading strategies which exploit the annual pattern earn significantly positive returns. Performance analyses shows that returns of such strategies are not explained by the three traditional Fama & French (1993) risk factors.

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Table of Contents

List of Figures

List of Tables

1 Introduction

According to the efficient market hypothesis, future stock returns cannot be predicted using historical information. However, there exists well-grounded work in the academic literature contradicting this hypothesis: De Bondt & Thaler (1985, 1987) document that past loser stocks from the preceding two to five year period tend to outperform past winner stocks in the following years. Jegadeesh (1990) and Jegadeesh & Titman (1993, 2001) show that there exists a momentum effect according to which stocks that were winners over the past 12 months outperform losers in the following month.

More recent research discovers seasonality patterns at an annual frequency: past same-calendar-month returns explain the variation in current-calendar-month returns to a considerable extent. This seasonality pattern is discussed by various research papers and is first observed by Heston & Sadka (2008). The authors show that expected returns of U.S. listed common stocks exhibit an annual pattern in the cross-section during the period from January 1965 to December 2002. Keloharju, Linnainmaa, & Nyberg (2016) extend this study to the U.S., using a sample ranging from January 1963 to December 2011, and confirm the findings of Heston & Sadka (2008). Heston & Sadka (2010) transfer their initial U.S. study to an international context, examining Canada, Japan, and 12 European countries, and again document significant annual seasonal effects.

The main question of the paper at hand is whether returns of German and Swedish listed common stocks follow a similar seasonality pattern. We use Fama & MacBeth (1973) regressions in order to examine if seasonality exists and if the effect varies across the two countries or across firm specifics, such as book-to-market ratio, company size, and industry affiliation. Further, the potential pattern is tested by generating a trading strategy: Taking a long position in stocks with high historical same-calendar-month returns while at the same time taking a short position in stocks with low historical same-calendar-month returns should earn a significantly positive return if seasonalities exist.

Compared to Heston & Sadka (2010), we extend the sample horizon by almost ten years, using a sample ranging from January 1986 to December 2015. This delivers important out-of-sample evidence and insights regarding annual patterns. Moreover, we conduct regression analyses separately for Germany and for Sweden, as well as for a combined sample of the two countries. Heston & Sadka (2010), on the contrary, only report results for a combined European sample and not on a country level. Additionally, we look at differences across firm specifics and industries by constructing various subsamples of the data. Such analyses have not yet been undertaken in the academic literature.

The outcome of this research is interesting for different reasons: (1) If a trading strategy based on historical same-calendar-month performance delivers positive returns, institutional or private investors could create portfolios based on such a strategy. (2) Even if investors are not explicitly trading on a seasonality strategy, the approach could influence their behavior, e.g. by delaying the sale of a historical winner stock to improve the performance of existing portfolios. (3) If returns of a seasonality strategy cannot be explained by common known risk factors such as market risk premium, size, and value, seasonality could prove to be a risk factor itself, which would be interesting for further academic research.

One of the main economic implications of such a pattern would be that stock markets seem to be inefficient to a certain degree: if past returns can predict future returns, and if a successful trading strategy can be implemented based on this information, this shows a market anomaly that cannot be explained logically. However, excess returns of a seasonality strategy might be wiped out by transaction costs, since trading based on annual historical month returns implies portfolio rebalancing every month.

The remainder of this paper is organized as follows: Section 2 gives an overview of existing literature on efficient markets and historical returns patterns. Section 3 introduces possible theoretical explanations for the existence of return seasonalities. Section 4 describes the data and the methodology used. Section 5 describes and analyzes the results of the regression analysis. Section 6 evaluates the robustness of the empirical approach. Section 7 reports the performances of various trading strategies, including strategies which exploit annual seasonality patterns, and reports risk-adjusted returns of the seasonality strategies. Section 8 concludes.

2 Related Literature

In order for the reader to get a better understanding of the seasonality effect, we present a brief overview of academic work previously conducted in the field of historical asset return patterns. First, we briefly introduce and review the concept of market efficiency and potential violations of it. Second, we describe the momentum and reversal strategies and their implications for market efficiency. The section is concluded with a review of former research on return seasonalities together with more recent findings in the field.

2.1 Efficient Market Hypothesis and Random Walk Theory

The efficient market hypothesis (EMH) states that a stock market is efficient if security prices fully reflect all available information at any point in time. Fama (1970) gathers and summarizes existing research on the EMH in a survey article and concludes that stock markets are efficient, mainly based on previously conducted tests of return autocorrelations at daily and weekly frequencies. At the time, the EMH was supposed to hold for whole stock markets as well as for individual securities. As a consequence, neither trading strategies that select stocks based on historical return information nor strategies that select stocks based on fundamental analyses should be able to generate higher risk-adjusted returns than a strategy that selects stocks randomly. According to the EMH, new information is incorporated into security prices instantaneously.

A concept which is strongly intertwined with the EMH is the idea that the formation of security prices follows a "random walk". In the finance literature, this idea states that subsequent price changes of securities are independent from each other and not predictable (Malkiel, 1973). A random walk implies that investors cannot outperform a broad-based market portfolio by selecting individual stocks based on any analysis since price changes are unpredictable.

Conducting tests on weekly return data, Lo and MacKinlay (1988) strongly reject the random walk hypothesis for weekly return indices, for size-sorted portfolios, and for individual stocks. Instead of a random walk price formation process, the authors report significantly positive serial correlation for both weekly and monthly security returns. The general acceptance of the EMH, and of the random walk hypothesis especially, became even more controversial with the emergence of empirical evidence which seemingly contradicted the assumption of unpredictable prices. Empirical studies show that it is possible to generate profitable trading strategies based on historical return information. This finding contradicts the weak form of the EMH, which states that historical returns do not contain information about future returns (Fama, 1991). Some of the most well-known trading strategies which use patterns in historical returns are presented in the following sections.

However, one has to keep in mind that the rejection of the random walk hypothesis does not necessarily implicate market inefficiency at the same time. That follows from the fact that statements about market efficiency are always conditioned on an asset pricing model which is used to test the efficiency, e.g. to test for abnormal security returns. This leads to a joint hypothesis problem: is the market inefficient or is the asset pricing model wrongly specified? For example, asset pricing models could incorporate time-varying risk premiums which would allow for rejecting the random walk hypothesis while not contradicting the EMH.

2.2 Momentum Strategies

One popular finding contributing to the market efficiency debate is the momentum anomaly. This anomaly was first documented by Jegadeesh and Titman (1993). Essentially, the study shows that for individual U.S. stocks past winners tend to outperform past losers significantly. Winner and loser stocks are identified during a preceding three- to 12-month formation period. The outperformance continues to persist over a subsequent three to 12-month holding period. Consequently, buying past winner stocks while selling past loser stocks represents a profitable trading strategy. The profitability of such individual stock momentum strategies is also documented internationally: momentum strategies are found to be profitable in 12 European developed stock markets (Rouwenhorst, 1998) and in emerging stock markets (Rouwenhorst, 1999). More recent research confirms previous evidence on momentum strategies and finds that profits associated with this strategy are positive in most large international markets (Chui, Titman, & Wei, 2010; Griffin, Ji, & Martin, 2003).

Jegadeesh and Titman (2001) extend their initial study on momentum by an additional nine years of data and show that the strategy continues to be profitable. This out-of-sample evidence for different sample periods and markets confirms the significance and persistence of the momentum effect.

Moreover, momentum strategies are not limited to individual stocks: there is empirical evidence that such strategies are profitable for country stock indices (Asness, 1997), for industry portfolios (Moskowitz & Grinblatt, 1999), for currencies (Menkhoff, Sarno, Schmeling, & Schrimpf, 2012; Okunev & White, 2003), for commodities (Erb & Harvey, 2006), and for bonds (Asness, Moskowitz, & Pedersen, 2013).

It is worth noting that the above mentioned momentum strategies are implemented in the cross-section of returns, thus the under- or overperformance of an asset relative to its peers. Additionally, it is possible to construct time series momentum strategies. These kinds of strategies use an asset's own past return in order to predict its future return. Moskowitz, Ooi, & Pedersen (2012) show that time series momentum is able to predict future returns for futures contracts on different asset classes. The authors report return continuation for one to 12 months and return reversals over longer time periods.

Momentum strategies do not have to be based on past returns (price momentum), but can also be based on fundamentals (earnings momentum). For example, see Givoly & Lakonishok (1979) for momentum strategies based on earnings forecasts, or Chan, Jegadeesh, & Lakonishok (1996) for strategies based on past earnings.

Noteworthy, returns of classical momentum strategies are risky in a sense that they are skewed with unlikely but strong and persistent periods of negative returns (Daniel & Moskowitz, 2011).

The robustness, statistical and economical significance, and persistence of the profitability of momentum strategies lead to the conclusion that compensation for risk is an unlikely explanation for the effect. This view is supported by findings that momentum is not explained by the Fama & French (1996) risk factors, nor by industry factors (Grundy & Martin, 2001). Additionally, Griffin et al. (2003) show that momentum in global markets is not related to global macroeconomic risk.

Consequently, researchers make use of behavioral models instead of risk-based models in order to explain the momentum anomaly. The literature considers investors' underreaction to new information as a source of momentum profits. Barberis, Shleifer, & Vishny (1998) argue that such an underreaction might stem from a conservatism bias which leads to an underweighting of new information. Another form of underreaction is the so-called disposition effect, which promotes that loss-averse investors are reluctant to sell their past losers while they sell their past winners (Grinblatt & Han, 2005). In contrast to the behavioral models, the joint examination of momentum and value returns across markets suggests that there might be a global, common risk factor (Asness et al., 2013). However, such a risk factor has not yet been identified by academic research.

2.3 Reversal Strategies

Another group of investment strategies which exploits patterns in historical return data are contrarian or reversal strategies. Such strategies buy past loser stocks and sell past winner stocks in order to profit from a mean reversion in stock returns. For NYSE-listed stocks De Bondt & Thaler (1985, 1987) document an underperformance of past winners relative to past losers of up to five years after the formation period. Because of the long time horizon, this strategy is categorized as a long-term reversal strategy. Similarly, there exists a short-term equivalent at the monthly frequency. Jegadeesh (1990) discovers that a reversal strategy which selects stocks based on their prior month performance and holds them for one month earns significantly positive returns during the period from 1934 to 1987. Related to those findings, Lehmann (1990) finds evidence for an even more short-term reversal effect: loser stocks in one week tend to outperform past winner stocks in the next week, thus experiencing substantial return reversals. As the short-term reversal strategy requires a lot of rebalancing, it will likely become unprofitable when transaction costs are taken into account.

One explanation for the profitability of such contrarian strategies is related to cognitive biases of investors. De Bondt & Thaler (1985) argue that investors overreact to good and bad news, which in turn leads stock prices to deviate from their fundamental values. Those deviations are later corrected through mean reversion. Nagel (2012) claims that the trading scheme of a contrarian investor resembles the trading of a market maker, providing a risk-based explanation. That is, selling stocks when prices are high and buying when prices are low. Thus, the return on the reversal strategy can be seen as the return of a liquidity provider. This interpretation is consistent with earlier work by Avramov, Chordia, & Goyal (2006), that shows that positive returns of reversal strategies are mainly attributable to trading in high-turnover, illiquid stocks.

2.4 Return Seasonalities

Different seasonal patterns in returns have been documented in previous finance literature. This section provides an overview of past work on return seasonalities and examines where seasonalities occur.

2.4.1 Seasonality in Stock Index Returns

A seasonality pattern in returns is first documented for an equally-weighted index of NYSE stocks (Rozeff & Kinney, 1976). The authors show that the average monthly return in January is higher compared to the one in other months during the period from 1904 through 1974. The equal weighting of stocks within the index leads to the conclusion that this seasonal effect is mainly driven by small firms. Keim (1983) finds that the size effect (Banz, 1981; Reinganum, 1983) is significantly stronger in the month of January than in any other month, with almost half of its excess return falling into January. The seasonal pattern of the "January effect" is also evident in 15 international stock markets of industrialized countries (Gultekin & Gultekin, 1983).

Related to this "January effect", other trading strategies such as the long-term reversal (De Bondt & Thaler, 1985), the short-term reversal (Jegadeesh, 1990), and the book-to-market effect (Loughran, 1997) exhibit significantly higher returns in January as well. In contrast, returns on the momentum strategy are significantly positive in all months except for January (Jegadeesh & Titman, 1993; Novy-Marx, 2012)

First attempts of explaining the "January effect" relate the abnormally high returns in January to tax-loss selling at the end of the tax year (Roll, 1983). However, a different study reveals that the tax-loss selling hypothesis cannot explain the "January effect" in its entirety: large January returns still persist for some firms even after cleaning the data for potential tax-loss selling effects (Reinganum, 1983). Institutional investors often engage in "window dressing", i.e. selling past loser stocks at the end of the year (causing a decline in stock prices) and buying them back in January (causing a rebounce in prices), a behavior which also might explain the "January effect" (Lakonishok, Shleifer, Thaler, & Vishny, 1991).

A different return seasonality pattern is explored by Bouman & Jacobsen (2002), who provide evidence that country stock market indices exhibit higher returns during the period of November to April. In contrast, returns are zero or even negative from May through October. Returns of those stock market indices thus show a seasonality pattern. The effect, which survives tests when controlling for the January effect, is persistent over time and appears in U.S., European and international stock markets.

Another study relates seasonal depression caused by shorter days during fall and winter months to stock market returns (Kamstra, Kramer, & Levi, 2003). This effect, known as "Seasonal Affective Disorder" (SAD), causes stock market returns to vary seasonally. It is also robust and documented for U.S., European and international markets.

2.4.2 Seasonality in Individual Stock Returns

The literature presented in the previous section focuses on seasonalities in returns of stock market indices and popular trading strategies. In contrast to that, more recent empirical work put an emphasis on seasonalities in individual stock returns in a more general context. Heston & Sadka (2008) use Fama-MacBeth (1973) regressions of monthly returns of NYSE- and AMEX-listed common stocks against their own lagged returns. In doing so, the authors document a seasonality pattern in the cross-section of expected stock returns. This pattern suggests that stocks are likely to exhibit relatively high or low returns in the same calendar month every year. The study confirms the results of Jegadeesh (1990), i.e. a short-term reversal effect of stock returns for the lag of one month and a positive momentum effect from lag 2 to 12. Moreover, the results are consistent with the previously documented long-term reversal effect (De Bondt & Thaler, 1985, 1987). New in Heston & Sadka (2008) are the positive estimation coefficients for every annual lag that disrupt the long-term reversals. This general periodic pattern of positive peaks at the annual frequency is persistent for up to 20 years.

The seasonality pattern is not confined to the U.S. stock market, but also evident in the cross-section of stock returns in Canada, Japan and 12 European countries (Heston & Sadka, 2010). This out-of-sample evidence speaks in favor of a robust seasonality effect and prevents the risk of academic data snooping (Lo & MacKinlay, 1990). Moreover, return seasonalities are not limited to individual stock returns. A recent study reveals similar return seasonalities in well-diversified portfolios which are based on characteristics such as size, value, momentum or industry (Keloharju et al., 2016). The seasonality pattern also exists in commodity returns (Keloharju et al., 2016), and in country portfolios (Heston & Sadka, 2010; Keloharju et al., 2016). Keloharju et al. (2016) also document seasonality effects in daily returns.

2.4.3 Seasonality Strategies

The previously mentioned momentum and reversal strategies are relying on a contiguous historical formation period during which cumulative returns are used to assign stocks into winner and loser portfolios. Those portfolios are then used as the long and short leg of the strategies. A fairly new category of trading strategies based on historical return patterns are annual seasonality strategies.

In contrast to momentum and reversal strategies, seasonality strategies only use past returns in periodic months in order to identify winner and loser stocks. The first work to introduce such a seasonality strategy for individual stocks is Heston & Sadka (2008). The authors construct different seasonality strategies and find that the top decile portfolio outperforms the bottom one by 0.5% per month on average. This outperformance is robust and persistent for up to 20 years during the period from 1965 through 2002. The study is conducted with common shares listed on the NYSE and AMEX. The same approach is also applied out-of-sample, using data on international stock markets for the period January 1985 to June 2006 (Heston & Sadka, 2010). A monthly seasonality strategy which picks stocks based on past same-calendar-month returns outperforms a non-seasonal strategy significantly. The outperformance lasts for up to five years in the Canadian, the Japanese and 12 European stock markets. The documented seasonality pattern survives tests when controlling for common risk factors like size or value (Heston & Sadka, 2008, 2010). Moreover, in the international study the different seasonality strategies exhibit low correlation across countries which contradicts the hypothesis that return seasonalities are due to global risk factors (Heston & Sadka, 2010). Heston & Sadka (2010) suggest that the seasonality effect could emerge from behavioral and institutional factors which are similar across stock markets. In a more recent paper however, a risk-based explanation for seasonalities is introduced: individual stocks are exposed to various risk factors and thus aggregate seasonalities across the different factors (Keloharju et al., 2016). This mechanism would explain why there is no sole risk factor responsible for return seasonalities. Keloharju et al. (2016) show the economic importance of return seasonalities by constructing different seasonality strategies for individual stocks, anomalies, commodities and stock indices. Those strategies are based on the performance of the different assets in the historical same calendar months and outperform strategies based on historical other calendar months significantly. The authors also take an asset management perspective and show that it is possible to increase the Sharpe ratio significantly when adding a "momentum-like" seasonality factor to the investment opportunity set, which initially only included market, size, value and momentum factors.

3 Potential Explanations for Return Seasonality Patterns

In order to compare results of our analysis with the existing literature, we introduce some theoretical explanations to illustrate different ideas of how seasonal return variations could be generated. We focus on the most recent work in this field, i.e. Heston & Sadka (2008, 2010) and Keloharju et al. (2016).

3.1 Seasonality Pattern in Heston and Sadka

Heston & Sadka (2008) mention two statistical explanations for seasonality patterns: (1) seasonal autocorrelation in monthly stock returns, and (2) cross-sectional variations in mean stock returns. Using data of the U.S. market, they recognize annual cross-sectional autocorrelation at lags of 12, 24, and 36 months as part of a general seasonality pattern that lasts up to 240 lags and explains a significant magnitude of the cross-sectional variation in mean stock returns. However, they mention that the autocorrelation would need to be extremely persistent to last for up to 20 years. The explanation of cross-sectional variations, proposed by Conrad & Kaul (1998), proves consistent with the seasonality pattern if there is large cross-sectional variation in mean stock returns that is dependent on the calendar month. Heston & Sadka (2008) find that seasonality explains a significant part of the cross-sectional variation in expected stock returns and that there is a significant effect when measuring the cross-section of expected stock returns across seasonal months.

Additionally, Heston & Sadka (2008) test if seasonality patterns are explained by trading volume and intra-month volatility. While both factors show similar seasonal patterns, they do not explain the seasonal effect in returns. Finally, the research finds that the seasonality pattern in returns is independent of size, industry, earnings announcements, dividends, and fiscal year.

In a subsequent international study, Heston & Sadka (2010) examine Canada, Japan and 12 European stock markets. Confirming their previous results, they find that the seasonality pattern remains after controlling for size, beta, or value. The authors also conclude that the strategies do not correlate across countries and thus do not reflect premiums for systematic global risks. Furthermore, they confirm that the annual seasonality pattern is not explained by common risk factors and mention that it may need to be explained by behavioral theories.

3.2 Aggregation Mechanism

In a model where expected excess returns entail a systematic part, Keloharju et al. (2016) argue that seasonal variation in security returns is caused by the seasonal variation in factor premiums to which securities are exposed. Since securities are likely to be exposed to more than one risk factor, even modest seasonality in an individual factor premium will eventually add up to large seasonality effects in security returns. The crucial assumption of this mechanism is that stocks are exposed to a number of different risk factors. Since the seasonality in security returns in this model arises from the seasonal variation in factor risk premiums, the factor premiums must be allowed to vary across months. The authors assume that factor risk premiums are specific for each calendar month and stay constant over time for that calendar month. It is then possible to show that any seasonal effects of the monthly factor premiums are transferred to the cross-section of security returns only if factor loadings in the cross-section vary across the different securities. Consequently, if all securities exhibited the same factor loadings, returns of all securities would get affected in the same way when factor risk premiums change and no seasonal pattern would be detectable in the cross-section of security returns. This is even the case when there is a seasonal variation in the factor premiums. Seasonality effects in the cross-section will be larger, the greater the number of risk factors securities are exposed to is, and the more dispersed securities with respect to factor loadings are.

In brief, return seasonalities in this model arise from systematic risk factors that all securities are exposed to. As a result, a seasonality effect would not be detected when controlling for stock-calendar month fixed effects, since seasonalities are due to expected returns.

3.3 Firm-specific Seasonalities

In contrast to the aggregation mechanism, return seasonalities could also be firm-specific. In this case, security returns do not depend on factor loadings or certain risk factors premiums. Security realized returns rather consist of a security's seasonally (monthly) varying expected return and a residual (Keloharju et al., 2016).

The authors show, on the one hand, that the cross-sectional autocovariances are always zero at non-annual lags. On the other hand, the cross-sectional autocovariances approach a constant in the idiosyncratic model at annual lags as the number of stocks increases. Since the variance in the cross-section is a constant, the variance of the cross-sectional autocovariance is zero in the time series. This is due to the fact that shocks to returns are all of idiosyncratic and not of systematic nature. The authors test this assumption by comparing the variances of two long-short strategies, i.e. a seasonality strategy and a random strategy. If the firm-specific seasonality model holds, the variances of both strategies should be more or less equal. Conversely, the variance of the seasonality strategy will be higher if the systematic model holds, because shocks hit the systematic risk factors and those get picked up in the strategy. Keloharju et al. (2016) confirm that the systematic model is more likely to hold as they find a higher variance in the seasonality strategy.

The seasonality effect would disappear if the Fama & MacBeth regressions control for stock-calendar month fixed effects. This is because seasonalities in this model result from seasonally varying expected returns of individual securities only (Keloharju et al., 2016).

3.4 Return Seasonalities due to Autocorrelated Innovations

Another potential explanation for return seasonalities focuses on a model with autocorrelated innovations. This model also assumes that seasonalities are firm-specific, but that they stem from autocorrelated residuals. Returns follow a process where the expected return of a security does not vary seasonally. The seasonal variation in security returns in this model specification arises from seasonality in the residuals, i.e. the time series autocovariance of the residuals is greater than zero when the same calendar months are considered, and zero for different calendar months. The assumption here is that expected returns are the same across securities and constant over time (Keloharju et al., 2016).

The model could be differentiated from the systematic model by comparing the variances of two long-short strategies. However, in this model, seasonalities would still remain, even after controlling for calendar-month fixed effects, since seasonalities stem from residuals.

According to Keloharju et al. (2016), among the different theoretical models, the systematic seasonality model is the most likely to hold. This is suggested by the comparison of the variances of a long-short seasonality strategy and a random strategy, as well as by the disappearance of seasonalities when they control for stock-calendar month fixed effects.

4 Empirical Approach

4.1 Data Description

In the course of our analysis, we use data from three different data sources: (1) Compustat Global Security Daily, (2) Compustat Global Fundamentals, and (3) Thomson Reuters Datastream.

The initially retrieved datasets from Compustat Global Security include daily price information for 1,776 German and 1,155 Swedish exchange-traded securities for the past 30 years, i.e. from 31 December 1985 to 31 December 2015. For our research purpose, we exclude the following from the initial data: (a) securities that are traded in any different currency than the local currencies, i.e. DEM and EUR for Germany and SEK for Sweden, (b) securities that are traded at any other exchange than one of the common stock exchanges in the respective country[2], thus excluding brokers, OTC, derivatives and future exchanges, (c) all non-common stocks such as exchange-traded funds, convertible securities and preferred stocks, and (d) securities with available data for less than 24 consecutive months. The remaining common stocks amount to 1,465 German and 697 Swedish companies.

Table 1 **Summary Statistics of Firms and Observations**

Table 1 shows the number of unique firms, the number of firm-month observations and the distribution of the number of months that firms exist in each sample.

Country	No. of Firms	24 <= Months <= 60	60 < Months <= 120	Months > 120	Firm-Month Observations
Germany	1,465	210	438	817	218,540
Sweden	697	202	274	221	77,950
Total	**2,162**	**412**	**712**	**1,038**	**296,490**

For these companies and the same time period, we further obtain the daily number of shares outstanding in order to calculate the market value of each company on any given day, the fiscal year-end book value of equity to be able to determine book-to-market ratios, fiscal year-end EBITDA and Net Sales to measure profitability, and an industry classification identifier according to the Global Industry Classification Standard (GICS). These data are extracted from Compustat Global Security Daily and Compustat Global Fundamentals. In case of multiple accounting data for the same fiscal year and firm, e.g. when a firm changes its fiscal year-end from December to March, we use the most recent data. Following Fama & French (1995), we additionally exclude negative book equity values.

[2] The included German stock exchanges are Berlin, Bremen, Dusseldorf, Frankfurt, Hamburg, Hanover, IBIS, Munich, Neuer Markt, and Stuttgart. The included Swedish stock exchanges are NOREX and Stockholm.

To attain comparable market values and monthly returns, all prices in the datasets are converted into USD, using the relevant daily exchange rates from Thomson Reuters Datastream, i.e. SEK to USD, EUR to USD and DEM to USD. As the originally retrieved data from Thomson Reuters does not include exchange rates for weekends or bank holidays, we use the exchange rate from the prior bank day for these dates. With the conversion to USD we follow the approach of Heston & Sadka (2010) and ensure to take the view of an outside investor, who does not prefer either of the two markets based on currency. Additionally, for the calculation of monthly returns, we adjust for stock splits and dividend payouts, both provided by Compustat Global Security Daily.

Finally, we winsorize the data to account for outliers and to limit extreme monthly returns. Therefore, positive returns above the 99.9th percentile are set equal to this threshold, i.e. 217.3% for Germany and Sweden combined (292 returns winsorized), 247.7% for Germany (215 returns), and 147.2% for Sweden (76 returns). Negative returns are not winsorized as they are limited to -100% per definition. Table 2 shows a summary of the returns per sample after winsorizing.

Table 2 **Summary Statistics of Returns**

Table 2 shows a summary of the winsorized monthly USD returns per sample, including its minimum, maximum, mean and standard deviation.

Sample	Minimum	Maximum	Mean	SD
Germany and Sweden	-99.8%	217.3%	0.77%	18.6%
Germany	-99.8%	247.7%	0.72%	19.5%
Sweden	-90.6%	147.2%	0.94%	16.7%

4.2 Critical Discussion of Data Sources

As we use Compustat by S&P Capital IQ and Thomson Reuters as data sources, we are confident that the data used is extracted from reliable and reputable data providers. S&P Capital IQ is a leading provider of data for academic and quantitative research, which is used by many notable researchers, e.g. Eugene Fama, Kenneth French, Steven Heston and Ronnie Sadka (Fama & French, 1992; Fama & French, 2008; Heston & Sadka, 2008). All data from Compustat are obtained via WRDS (Wharton Research Data Services).

However, it should be mentioned that data available for Germany and Sweden are far more limited than for the United States. First, the markets are considerably smaller with currently c.1,300 listed companies in Germany and Sweden[3] compared to more than 4,000 in the United States[4].

[3] Listed companies as of December 2015: 797 in Germany, 532 in Sweden (Compustat Global Security Daily)
[4] Listed companies as of December 2015 in the U.S.: 4,381 (The World Bank, 2016)

Second, the data is available for a shorter period of time: Compustat begins its data coverage in December 1985, while the CRSP U.S. stock databases start with the coverage of the NYSE in 1925[5]. Thus, most of the already existing research uses greater datasets with more observations, e.g. Keloharju et al. (2016) (all NYSE, Amex, and NASDAQ stocks for over 49 years). This proves especially critical when we examine subsets, e.g. companies of one specific industry in Sweden, since there might not be enough data available to obtain significant results, particularly for regressions using longer lags.

4.3 Methodology

In order to identify and evaluate return patterns in German and Swedish equities, we use univariate Fama & MacBeth (1973) cross-sectional regressions on monthly returns of individual stocks, following Keloharju et al. (2016).

Our study analyzes the combined sample of Germany and Sweden as well as the two individual samples. Additionally, all of the three samples are split in the following subsets: (1) three sets for value firms, growth firms, and firms that are neither value nor growth, measured by book-to-market ratio, (2) two sets for big and small firms, measured by market capitalization, (3) three sets for high, middle, and low profitability firms, measured by EBITDA over Net Sales, (4) two sets for last-month winner and loser firms, measured by last-month return, and (5) eight sets of firms according to their industry affiliation. Additionally, in order to test the robustness of our results, we (a) split the joint as well as the two individual datasets in a first and a second half, i.e. years 1986-2000 and years 2001-2015, (b) assess the three samples without January, and (c) conduct multiple regressions where coefficients at different annual lags are estimated at the same time.

For each of the above described samples and subsets, we regress returns in month *t* against returns in month *t-k*, using $r_{i,t} = a_{k,t} + b_{k,t}r_{i,t-k} + e_{i,t}$, where $r_{i,t}$ represents the return of stock *i* in month *t* and $r_{i,t-k}$ the return of the same stock in month *t-k*. The regression is computed for every month *t* from February 1986 to December 2015 (359 months) and for each lag *k* from 1 to 120. By including all firms with returns available in both month *t* and month *t-k*, we avoid sample selection and build feasible samples that do not suffer from hindsight bias. We estimate the slope coefficients as time series averages of $b_{k,t}$ over all available months *t* in order to examine if coefficients for annual lags are significantly higher than coefficients for other months.

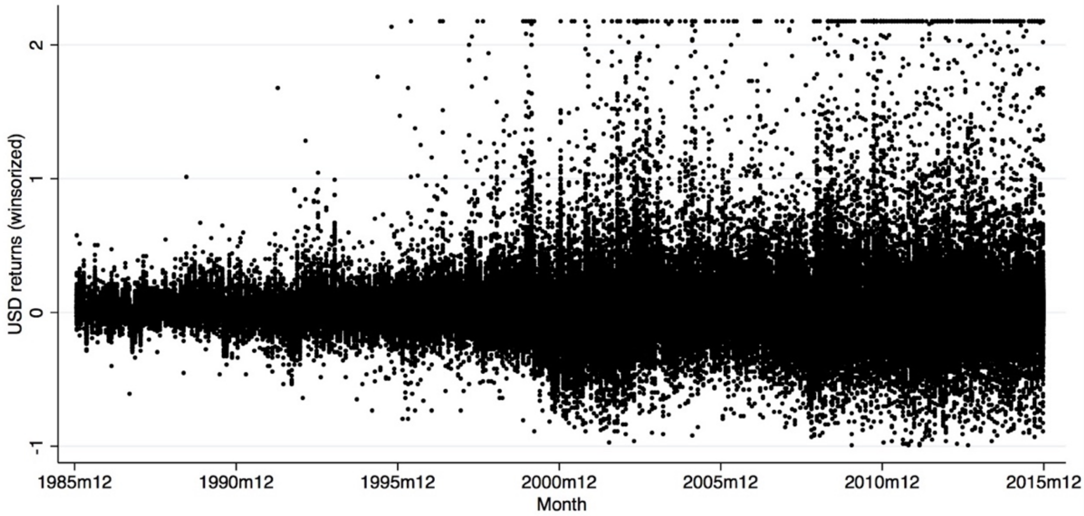
As can be seen in Figure 1, the variance of returns is not constant over time. Additionally, there is an assumed serial correlation between monthly returns of the same firm which leads to autocorrelated standard errors. To adjust for the heteroscedasticity and the autocorrelation, we

[5] CRSP - The Center for Research in Security Prices, 2016

compute all regressions using the Newey & West (1987) correction with 12 lags. This approach is common in recent research, such as Heston & Sadka (2008).

Figure 1 **Winsorized Monthly Returns, January 1986 to December 2015**

Figure 1 shows the monthly USD returns across Germany and Sweden, after adjusting for outliers by winsorizing positive returns at the 99.9th percentile.



5 Empirical Results

5.1 General Observations

While specific observations for all subsets as well as the difference between Germany and Sweden within the sets are discussed in the following sections, some general observations can be made for every subset. First, the first lagged month always shows a negative estimated coefficient, where significant (above 90%), while most other significant coefficients from lag 2 to 12 are positive. This is consistent with previous studies such as Jegadeesh (1990), who finds significantly negative first-order correlation of stock returns (short-term reversal effect) and significantly positive correlation at lags up to 12, and Jegadeesh & Titman (1993, 2001), who show that U.S. stocks that perform well (poorly) over three to 12 months tend to continue to perform well (poorly) in the following three to 12 months (momentum effect). Second, estimated coefficients tend to decrease in the following months after lag 12, showing signs of long-term reversals, often with positive peaks at every annual lag. If such annual positive peaks are observable and the majority is significant at the 90% level, we specify this as an annual seasonality pattern. Third, while the appearance and magnitude of such a pattern varies across subsets, it is generally stronger in Sweden than in Germany. This proves especially true when narrowing the data to smaller sets.

Comparing our results to Keloharju et al. (2016), we find that the patterns in the German and Swedish markets are weaker than in the U.S., however, that the trends, i.e. the negative first-order correlation, the momentum effect between lag 2 to 11, the lower coefficients for longer non-annual lags, and the peaks at annual lags, are similar. As mentioned in chapter 4.2, we suffer from having less data available for Germany and Sweden, which generally leads to slightly more disrupted patterns and less significant estimates, particularly for smaller subsets and at longer lags. Because of the smaller data available, we measure significance at a 90% confidence level, when not specified otherwise.

5.2 All Firms

When examining the combined sample of all firms for Germany and Sweden, we find seasonality patterns: Seven out of the ten annual estimates are significantly positive (at lags 12, 24, 36, 48, 72, 84, and 108). Consistent with the momentum effect, coefficient estimates from lags 2 to 11 are positive, but smaller than the estimate at lag 12. As can be seen in Figure 2, Panel A, all annual estimates apart from the one at lag 120 are positive, while non-annual estimates after lag 12 are mostly negative or close to zero. The only noticeable disruptions[6] from this annual pattern can be found around lag 60 and lag 120: While estimates at lags 59 and 61 are significantly positive, the one for lag 60 is not. The estimate at lag 119 is also significantly positive, whereas the one at lag 120 is insignificantly negative.

In Germany, the overall pattern is similar, also showing a negative estimate at the first lag, positive estimates from lag 2 to 11, and mostly negative estimates afterwards, which are interrupted by positive peaks at annual lags (see Figure 2, Panel B). However, the pattern is clearly not as strong as in the combined sample: The number of significantly positive estimates at annual lags decreases to five out of ten (lags 12, 24, 72, 84, and 108) and all annual estimates apart from the ones at lag 96 and 108 are lower than in the combined sample. Additionally, the disruption around lag 60 is stronger, and the estimate at lag 120 is even more negative (however, still statistically insignificant).

On the contrary, Sweden shows a strong seasonality pattern with significantly positive estimates at every annual lag up to lag 72 and at lags 108 and 120 (see Figure 2, Panel C). While there is also some disruption in the Swedish pattern, it is not particularly concentrated around one year and the estimates for these disruptions are smaller than the significantly positive estimates at annual lags. Additionally, the estimate at the annual lag 120 is significantly positive. We also find the negative first-order correlation, the momentum effect, and the long-term reversal to hold in Sweden. The stronger annual seasonality pattern in Swedish stocks is especially interesting, since

[6] Throughout the results section, disruptions are specified as significantly positive non-annual estimates beyond lag 12.

the Swedish sample is the smallest one and should thus be exposed to a lower number of different risk factors.

Detailed regression outputs for each sample are reported in Appendix A, Table I.

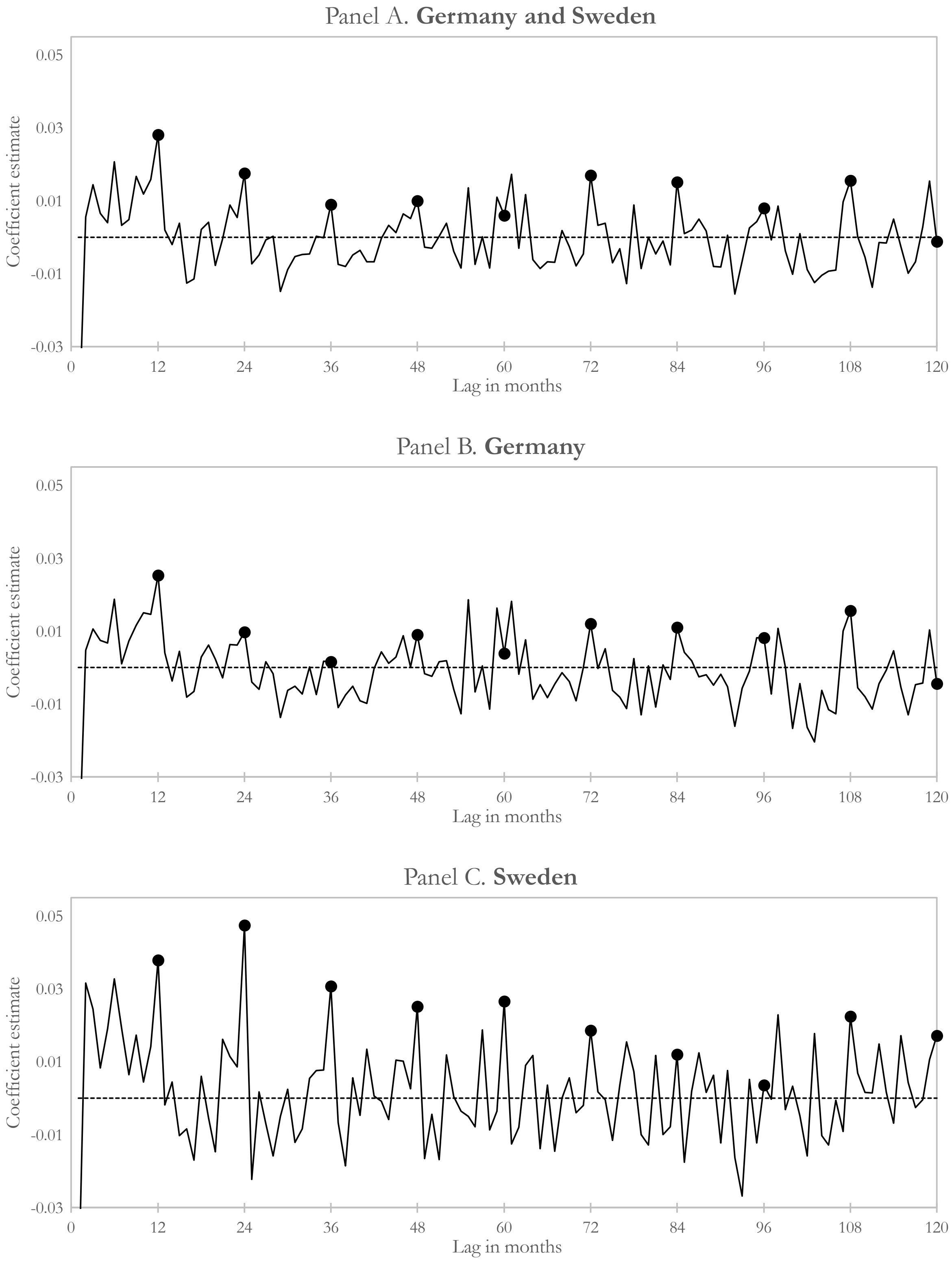


Figure 2. Cross-sectional regressions of monthly returns. Monthly univariate Fama MacBeth (1973) regressions of the form $r_{i,t} = a_{k,t} + b_{k,t} r_{i,t-k} + e_{i,t}$, are calculated for each month *t* and lag *k*, and where $r_{i,t}$ is the return of stock *i* in month *t*. The lagged variable $r_{i,t-k}$ is the return of stock *i* in month *t-k*. The regression is calculated for every month *t* from February 1986 through December 2015 (359 months), and for lag *k* values $1 - 120$. Figure 2 plots the time series averages of $b_{k,t}$. The analysis includes listed common stocks from Germany and Sweden (Panel A), Germany only (Panel B), and Sweden only (Panel C).

In the following sections, we split the combined sample as well as both the German and the Swedish sample in subsets. These sections are organized as follows: First, we explain the reason for assessing the specific group of subsets and the methodology used to classify the firms in each subset. Second, we summarize the empirical observations for each subset and outline differences between the combined sample, Germany, and Sweden. Third, we highlight the most important observations and compare between subsets.

While it will prove true that Sweden shows a stronger annual seasonality pattern in almost every subset, we discover that the difference between the two countries varies across the sets. Detailed regression outputs for each subset are always reported in Appendix A.

5.3 Value, Growth, and Other Firms

A number of previous studies shows return anomalies in connection with the book-to-market ratio (book value of equity over market value of equity). Rosenberg, Reid, & Lanstein (1985), Chan, Hamao, & Lakonishok (1991), and Fama & French (1992) all find abnormal high average returns for stocks with high book-to-market ratios. Thus, we classify three categories of firms for each of the three samples, i.e. the combined sample, the German, and the Swedish one. Value firms are considered as firms with the highest book-to-market ratios, growth firms as firms with the lowest book-to-market ratios, and other firms as firms that fall in neither of the two categories (middle book-to-market ratios). Following Fama & French (1993) and Keloharju et al. (2016), we define value firms as the top 30% of each sample and growth firms as the bottom 30%. Consequently, we classify value (growth) firms in each sample separately. As common in previous research (see Keloharju et al., 2016), in order to time accounting to market information, we use the book value of equity from the fiscal year ending in calendar year *t-1* and the market value of equity at the end of December of year *t-1* for the calculation of the book-to-market ratio. Each firm is newly classified as either value, growth or other firm every year in January and remains in this category throughout the year. For value firms, we regress the month *t* return on the return in month *t-k*, when the firm is a value firm in the year that contains month *t*. Consequently, a firm is not required to be a value firm in preceding years. We use the same approach for growth and other firms. This might lead to some inconsistency, however, if we require a firm to remain in the same category up to lag *k*, available observations would shrink drastically.

Assessing value firms, we find no significant annual seasonality pattern in any of the samples (only two significantly positive annual estimates in the combined sample, one in Germany, and three in Sweden). The pattern for the combined sample can be seen in Figure 3, Panel A-I, and the patterns for Germany and Sweden in Appendix B, Figure I, Panel B-I and C-I. Compared to the samples with all firms, the short-term reversal, i.e. the negative first-order estimate, is now only significantly observable in the combined sample and in Sweden, and the momentum effect, i.e. positive estimates between lag 2 to 11, is only slightly observable in Sweden, while it disappears almost completely in the combined sample and in Germany. Overall, Sweden thus shows the highest tendency to seasonal patterns, however, the small sample size of on average only 11,428 observations per lag clearly impacts statistical significance.

For growth firms, the picture is similar: none of the samples show a significant annual pattern, and Sweden even loses its slight tendency towards an annual pattern, as it now shows only two significantly positive estimates at annual lags. However, in the combined sample we find three significantly positive annual estimates at lags 12, 24, and 36 (see Figure 3, Panel A-II), while the estimates at these lags are not significant in the value firms set. Nonetheless, due to the short appearance this is not considered a significant annual pattern. Additionally, there is no sign of the short-term reversal effect, compared to a strong short-term effect in the value set. The short-term reversal effect also disappears in Sweden, which shows the strongest effect in the value set. In Germany, however, the negative first-order estimate changes from slightly insignificant to significant. The momentum effect is again only slightly observable in Sweden. The estimation coefficients for Germany and Sweden are plotted in Appendix B, Figure I, Panel B-II and C-II.

We also examine firms that are in between value and growth (middle 40%). In the combined sample, these firms show an annual pattern with five significantly positive annual estimates (at lags 12, 48, 60, 72, and 108) and limited disruptions[7]. As can be seen in Figure 3, Panel A-III, this contributes to a much clearer annual pattern than in the other sets. This is also observable in the German sample, where we find five significantly positive annual estimates (at lags 12, 48, 72, 96, and 108) and only four disruptions (see Appendix B, Figure I, Panel B-III). In Sweden, however, we still cannot find any significant annual pattern (see Appendix B, Figure I, Panel C-III). Compared to value and growth firms, we now see a significant short-term reversal and a significant momentum effect in every sample.

Given that the number of observations for firms in the middle category is larger across all samples, it is no surprise that the significance of patterns in this category is higher compared to value and growth firms. Nevertheless, for the combined sample and for Germany, the seasonality pattern in the middle set is substantially stronger, which cannot only be attributed to the larger sample sizes. Assessing the difference between value and growth firms, we find that growth firms show a higher number of significantly positive estimates at annual lags and less disruptions in the combined sample.

[7] Five compared to eight in the set of all firms.

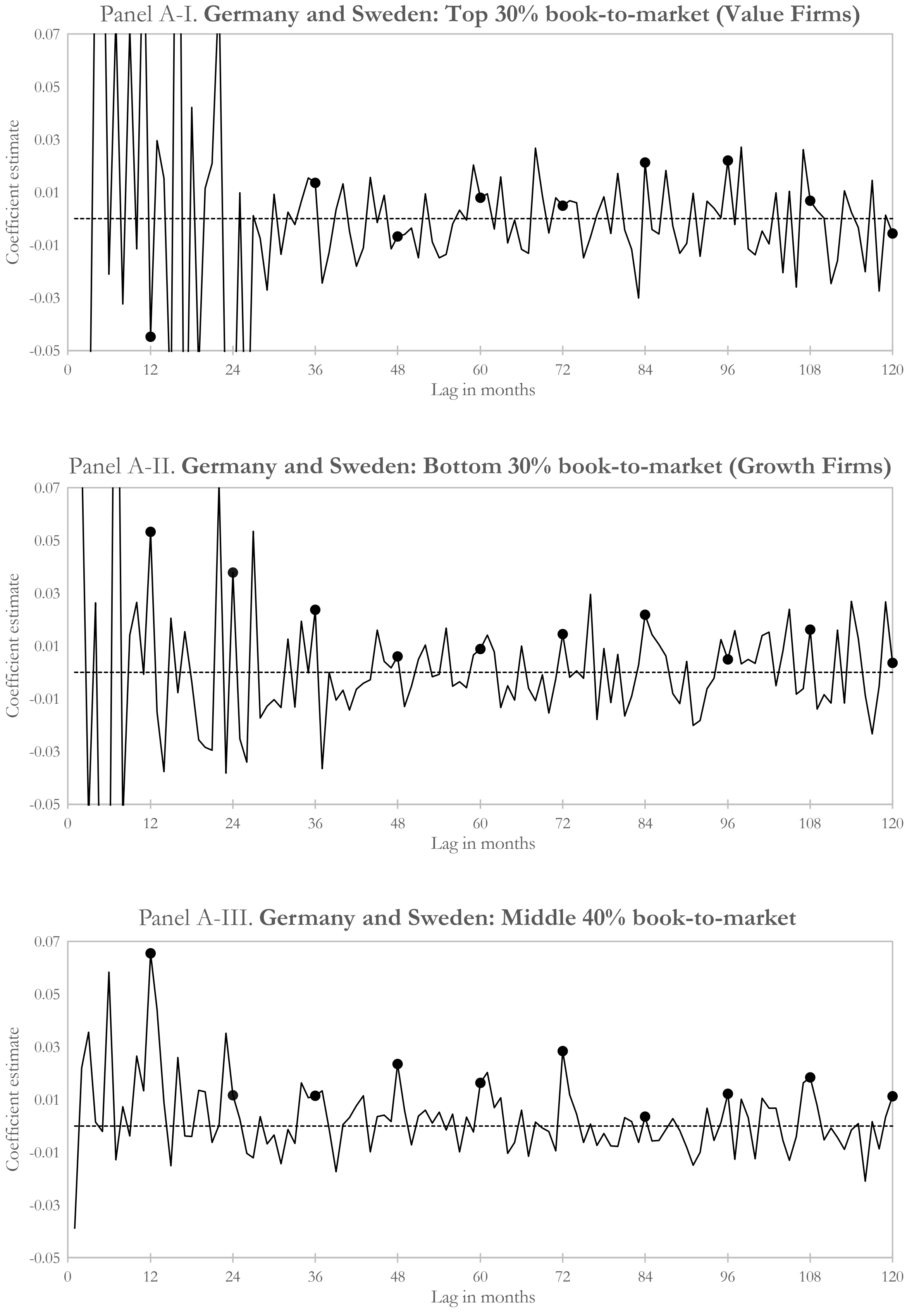


Figure 3. Cross-sectional regressions of monthly returns. Monthly univariate Fama MacBeth (1973) regressions of the form $r_{i,t} = a_{k,t} + b_{k,t}r_{i,t-k} + e_{i,t}$, are calculated for each month *t* and lag *k*, and where $r_{i,t}$ is the return of stock *i* in month *t*. The lagged variable $r_{i,t-k}$ is the return of stock *i* in month *t-k*. The regression is calculated for every month *t* from February 1986 through December 2015 (359 months), and for lag *k* values $1 - 120$. Figure 3 plots the time series averages of $b_{k,t}$. The analysis includes listed common stocks from Germany and Sweden, classified in value firms (Panel A-I), growth firms (Panel A-II), and other firms (Panel A-III).

5.4 Big and Small Firms

The size of firms can have a significant effect on average stock returns. For example, Banz (1981) discovers a strong negative relation between average stock returns and firm size measured by market capitalization. We calculate the market capitalization as stock price in USD times number of shares outstanding at the beginning of each month. Big firms are classified as firms with a market capitalization of at least the median market capitalization for that month (top 50%) and small firms as firms with a market capitalization of up to the median (bottom 50%). Thus, for an odd number of firms in one month the firm with the median market capitalization is included in both the big and the small category. Firms are classified for each sample separately. Consistent with the approach for value and growth firms, we regress returns of all firms that are small (big) in month *t* on returns of month *t-k* (where data is available), independent on whether those firms are small (big) in month *t-k*.

The seasonality pattern for big firms is strong across all samples. The combined sample (Figure 4, Panel A-I) clearly shows a seasonality pattern with seven significantly positive estimates (at lags 12, 24, 72, 84, 96, 108, and 120) and only five disruptions. The pattern in Germany (Figure 4, Panel B-I) is similar, with six significantly positive annual estimates (at lags 12, 72, 84, 96, 108, and 120) and only four disruptions. For the combined sample's big firms, as well as for Germany's big firms, the disruptions are also not particularly concentrated around one specific year. For Sweden's big firms (Figure 4, Panel C-I) the annual pattern is also significant, showing five significantly positive estimates (at lags 12, 24, 36, 60, and 120) and only one disruption. Given that Sweden's sample size is significantly smaller than the other two samples[8], the strong pattern in Sweden is even more remarkable. The annual pattern is more visible during the first 60 lags in Sweden, while it is stronger at longer lags (72 and beyond) in Germany and in the combined sample. This also can be attributed to the smaller Swedish sample, where especially longer lags only contain a small number of observations. Additionally, big firms show a strong momentum effect across all samples, and particularly in Germany, where every estimate from lag 2 to 11 is significantly positive. However, the short-term reversal effect for big firms is only significant in Sweden.

In contrast, small firms show a strong and significant short-term reversal at lag 1 across all samples. Compared to big firms, the momentum effect is similar in Sweden, but considerably less significant in the combined sample and in Germany. More importantly, all three samples show no significant annual seasonality pattern. While there is a weak pattern of up to four years in the combined sample (see Figure 4, Panel A-II), it disappears thereafter and even shows a significantly

[8] On average only 26,373 observations per lag, compared to 74,787 in Germany and 101,149 in the combined sample (compare Appendix A, Table V).

negative estimate at lag 120. Looking at Germany and Sweden separately, none of the countries show an annual pattern (see Figure 4, Panel B-II and C-II).

Compared to big firms, small firms have considerably less observations for longer lags as small firms exist for a shorter time in every sample. In the combined sample the number of observations per month decreases by less than 80,000 for big firms, but by more than 100,000 for small firms from lag 12 to lag 120. Thus, the weaker magnitude of the seasonality pattern in small firms can also be related to the fact that seasonalities are weaker when the stocks in the sample are exposed to a lower number of different risk factors and a lower variance in factor loadings of the firms (see chapter 0), which is more likely for smaller samples. However, given the fact that the set of small firms in the combined sample, as well as in Germany, would be large enough to show significant results but instead shows no significant annual pattern, while the set of big firms shows a significant pattern in all three samples, we conclude that seasonalities are clearly stronger for big firms. This is also emphasized by the strong pattern in Sweden's big firms, even though the number of observations in this set is significantly lower than in either of the sets for the combined sample's small firms or for Germany's small firms.

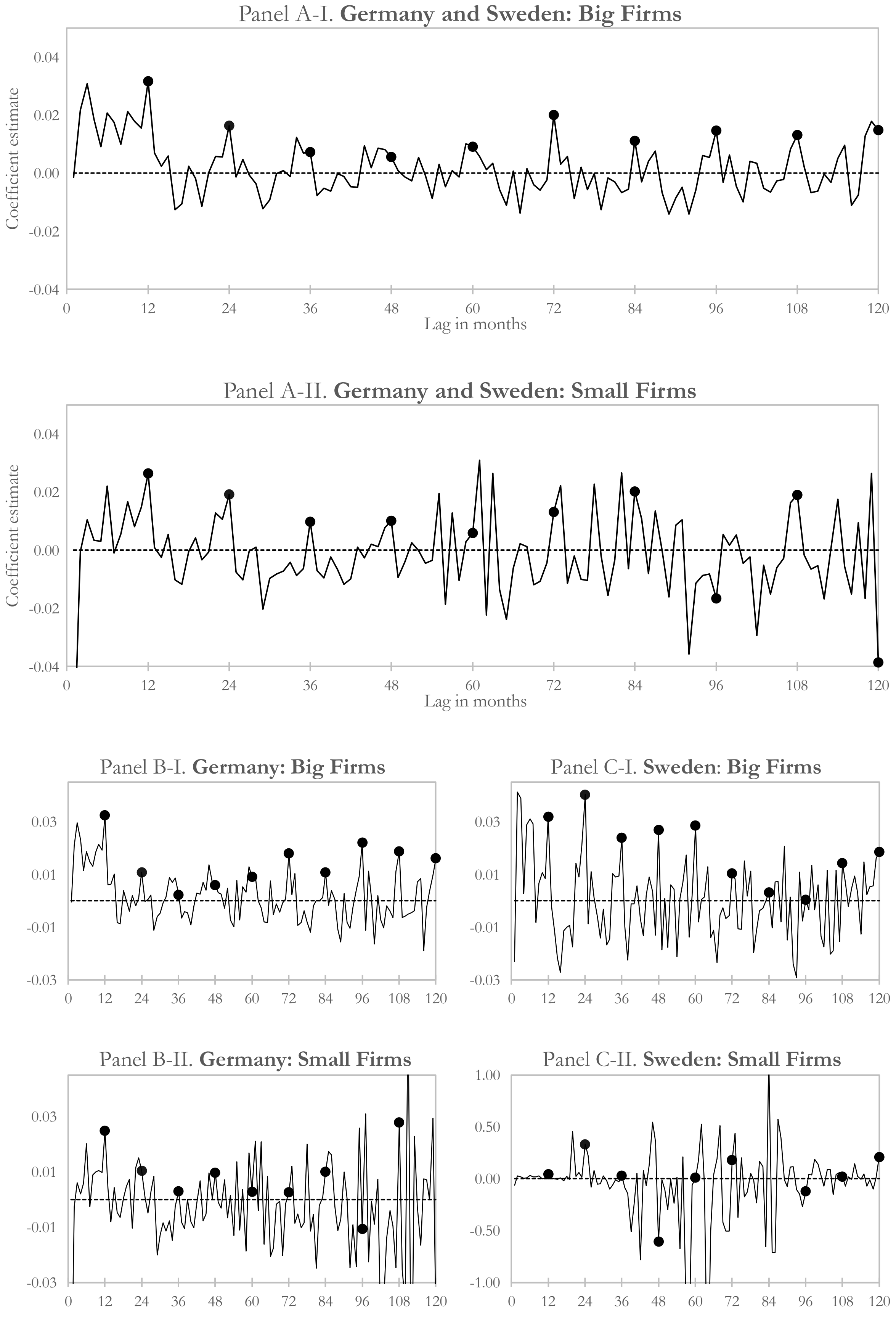


Figure 4. Cross-sectional regressions of monthly returns. Monthly univariate Fama MacBeth (1973) regressions of the form $r_{i,t} = a_{k,t} + b_{k,t}r_{i,t-k} + e_{i,t}$, are calculated for each month *t* and lag *k*, and where $r_{i,t}$ is the return of stock *i* in month *t*. The lagged variable $r_{i,t-k}$ is the return of stock *i* in month *t-k*. The regression is calculated for every month *t* from February 1986 through December 2015 (359 months), and for lag *k* values $1 - 120$. Figure 4 plots the time series averages of $b_{k,t}$. The analysis includes listed common stocks from Germany and Sweden, classified in different panels according to the subset used.

5.5 High, Middle, and Low Profitability Firms

When we examine big and small firms, we find that small firms show a weaker seasonality pattern than big firms. This is especially interesting since small firms usually achieve higher average returns (Banz, 1981). Haugen & Baker (1996) and Cohen, Gompers, & Vuolteenaho (2002) find that more profitable firms also achieve higher average stock returns. In order to assess if profitability has an effect on the appearance and intensity of seasonality patterns, we analyze high, middle and low profitability firms separately. Therefore, we define profitability as EBITDA over Net Sales and classify high profitability firms as the top 30% and low profitability firms as the bottom 30%. Since accounting data is available only on a yearly basis, we use EBITDA and Net Sales from fiscal year *t-1* in order to assign each firm to either high, middle or low profitability in year *t*. We thus define the firms as high, middle or low profitability firms for the whole year *t* only dependent on the performance in fiscal year *t-1*, and independent from the performance in the years before. The yearly classification is created for each of the three samples separately.

For high profitability firms, we cannot find any significant annual pattern in neither of the samples. Interestingly, the smallest set of Swedish high profitability firms shows two significantly positive annual estimates (at lags 24 and 48), while Germany shows only one (at lag 12) and the considerably larger combined sample also shows only two significantly positive annual estimates (at lags 12 and 36). Nevertheless, the number of these estimates is not high enough to prove an annual pattern in any of the samples. We find no significant short-term reversal in the combined sample and in Germany. The short-term reversal also disappears in Sweden, which is noteworthy as this effect is normally rather persistent in Sweden. However, while not significantly, the first-order estimate in Sweden is still more negative than in the combined sample or in Germany. The momentum effect is strong in the combined sample and in Germany, but weaker in Sweden. We attribute the non-existence of a significant short-term reversal and the weaker momentum effect in Sweden mainly to the smaller sample size.

Low profitability firms also do not show an annual pattern, however, here it is more similar across the three samples with only two significantly positive estimates in the combined sample (at lags 12 and 36), and only one in each Germany and Sweden (at lag 12, and at lag 24, respectively). We now find the negative first-order estimate to be significant in each of the samples, while the momentum effect is almost non-existent (only two significantly positive estimates from lag 2 to 11 in the combined sample, zero in Germany, and one in Sweden).

Finally, we look at firms with a profitability ratio between the top and the bottom (middle 40%). Even though for every sample this set naturally consists of the highest number of firm-month observations at each lag, we cannot identify an annual seasonality pattern in either of the samples. Again, Sweden shows the same number of only three significantly positive annual estimates as does the combined sample, while Germany shows one. We find that neither the combined sample nor the German sample show any significant estimate up to lag 48, which implies no significant short term reversal or momentum effect. In fact, many of the lags between 2 and 11 months are negative in these two samples, thus even contradicting the momentum effect (however, not significantly). In contrast to that, Sweden shows both a significant short-term reversal as well as a momentum effect. This combined with the fact that Sweden displays the same number of significant annual estimates as the combined sample is especially interesting, since it is once again the smallest sample.

Concluding from the fact that there is no significant annual pattern in neither of the three sets, we believe that splitting the samples based on profitability leads to sets that include firms with similar risk factor exposure, thus reducing seasonalities. As all annual effects are limited and there is no significant difference between the sets, detailed graphs and results are shown in the appendix only, i.e. Appendix A, Table VII-IX, and Appendix B, Figure II and III. While we also cannot find significant patterns in Sweden, we still observe that seasonalities are generally stronger. Even though it is the smallest set across all categories, it still shows the same number of significant annual estimates as the combined sample for high and middle profitability firms and a stronger short-term reversal and momentum effect for middle and low profitability firms. The small sample size, on the other hand, clearly limits statistical significance.

5.6 Last-Month Winner and Loser Firms

Many of our classifications are based on previous research that connects firm specifics with performance. Thus, we now test if seasonality patterns are different across differently performing stocks. For this purpose, we classify winner and loser firms every month based on their last month return, for each of the three samples separately. We classify a firm as winner (loser) firm in month *t* if its return in month *t-1* exceeded (fell short of) the average return across all firms in the respective sample in month *t-1*.

Last-month winners show a strong short-term reversal and momentum effect across all samples with a significantly negative first-order estimate and at least seven significantly positive estimates between lag 2 and 11. For Germany and Sweden combined (Figure 5, Panel A-I), the momentum effect is stronger than in the sample including all firms. We also observe an annual pattern with five significantly positive annual estimates (at lags 12, 24, 48, 72, and 84). However, this annual pattern is weaker than for all firms. It shows a lower number of significantly positive estimates at annual lags, a higher number of disruptions and a significantly negative estimate at lag 120. In Germany (Figure 5, Panel B-I), we see a similar effect: the momentum effect is clearly stronger compared to its all firms sample, and the annual pattern is weaker (with four significantly positive annual estimates). In Sweden (Figure 5, Panel C-I), however, the annual pattern not only weakens but almost disappears. We only find three significantly positive annual estimates and a higher number of disruptions. Contrary to the combined and German sample, we also find no significant increase in the magnitude of the momentum effect.

Last-month losers also show a significant short-term reversal, which compared to last-month winners is considerably stronger in the combined sample (Figure 5, Panel A-II) and in Germany (Figure 5, Panel B-II), while it stays rather similar in Sweden (Figure 5, Panel C-II). However, the momentum effect decreases substantially across all samples, and even disappears in Germany. The combined sample shows an annual pattern with five significantly positive annual estimates (at lags 12, 24, 72, 84, and 108). The pattern is somehow stronger compared to last-month winners with less disruptions and a positive estimate at lag 120 (however, not significant). In Germany, the annual pattern is slightly weaker as the one of last-month winners and shows only three significantly positive annual estimates. In Sweden, on the contrary, the pattern is clearly stronger when we compare to last-month winners. We find five significantly positive annual estimates with only two disruptions. The pattern is only visible during the first 60 lags. The non-appearance of significant annual estimates at longer lags can be attributed to the small number of observations at these lags.

All annual patterns, both in last-month winners as well as in last-month losers are weaker than in the samples including all firms due to the smaller sample sizes. When comparing last-month winners with last-month losers, we find a difference between Germany and Sweden: While Sweden clearly shows stronger annual seasonalities for last-month losers, this cannot be observed in Germany, where the pattern is slightly stronger for last-month winners. When looking at the combined sample, we cannot identify a noteworthy difference between last-month winners and last-month losers. Interestingly, in the combined sample and in Germany, last-month winners show a considerably stronger momentum effect, but a weaker short-term reversal effect. This is true when comparing to last-month losers as well as when comparing to the respective all firms sample. In Sweden, the change in the momentum effect can also be observed, however not as strong. The change in the reversal effect is not existent, as the magnitude is similar across all Swedish subsets.

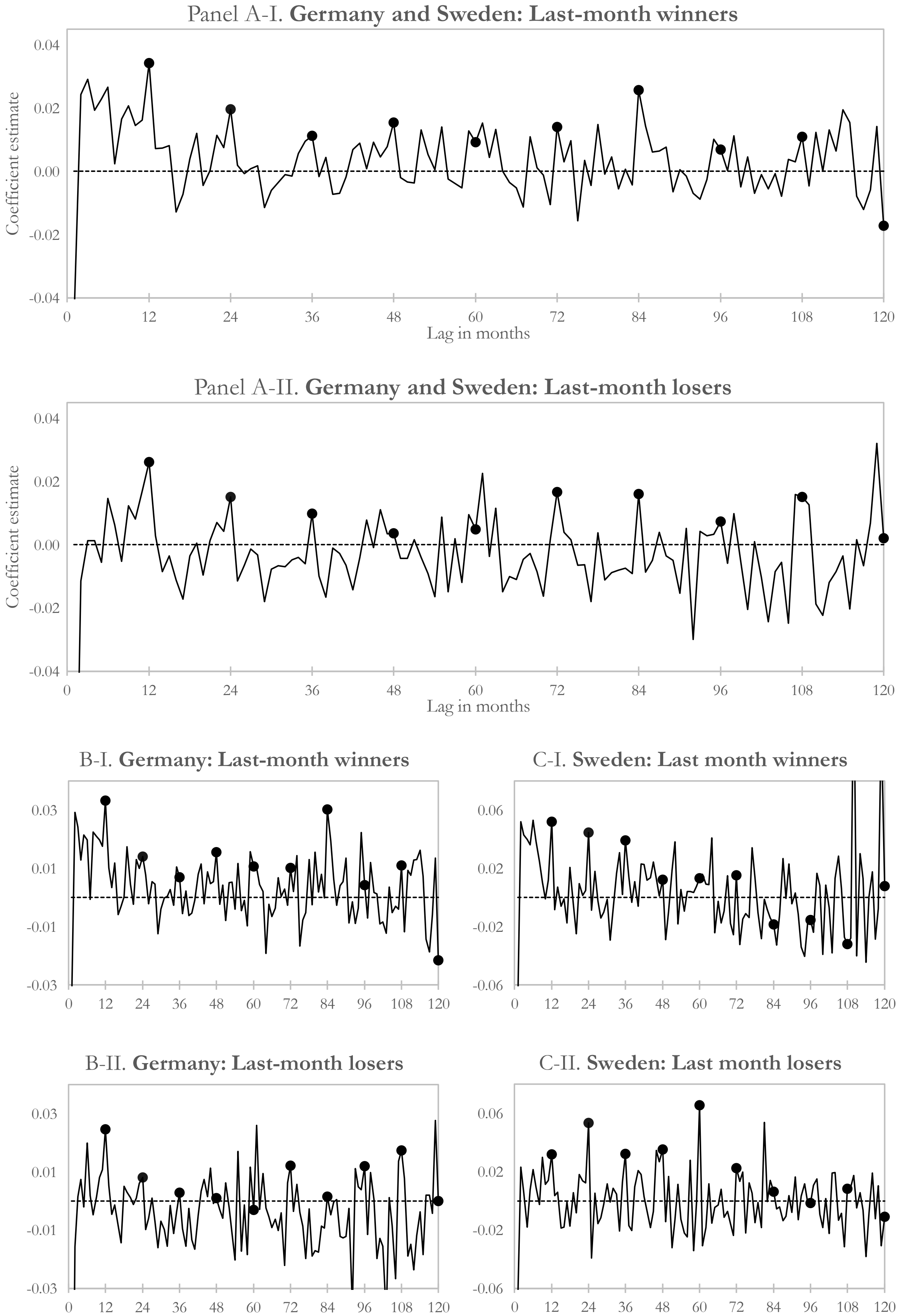


Figure 5. Cross-sectional regressions of monthly returns. Monthly univariate Fama MacBeth (1973) regressions of the form $r_{i,t} = a_{k,t} + b_{k,t}r_{i,t-k} + e_{i,t}$, are calculated for each month *t* and lag *k*, and where $r_{i,t}$ is the return of stock *i* in month *t*. The lagged variable $r_{i,t-k}$ is the return of stock *i* in month *t-k*. The regression is calculated for every month *t* from February 1986 through December 2015 (359 months), and for lag *k* values $1 - 120$. Figure 5 plots the time series averages of $b_{k,t}$. The analysis includes listed common stocks from Germany and Sweden, classified in different panels according to the subset used.

5.7 Industries

Finally, we categorize all firms according to their industry affiliation. We use the eleven sectors from the Global Industry Classification Standard (GICS): (1) Energy, (2) Materials, (3) Industrials, (4) Consumer Discretionary, (5) Consumer Staples, (6) Health Care, (7) Financials, (8) Information Technology, (9) Telecommunication Services, (10) Utilities, and (11) Real Estate. However, to increase sample size for each industry classification, we combine the following sectors to one industry each: (1) Energy with (10) Utilities; (4) Consumer Discretionary with (5) Consumer Staples; and (9) Information Technology with (10) Telecommunication Services. Thus, we end up with eight distinct industry classifications, i.e. industries (1) Energy & Utilities, (2) Materials, (3) Industrials, (4) Consumer, (5) Health Care, (6) Financials, (7) IT & Telecommunications and (8) Real Estate. Table 3 provides a summary of how many firm-month observations are available for each industry for different lagged returns.

Before we start to describe and analyze our results, we would like to point out some shortcomings concerning the data, more specifically the sample size. First, since the Swedish stock market does not include an excessive number of firms to begin with, slicing up the sample into different industries clearly reduces the statistical power of the undertaken regressions. This also applies to Germany but to a lesser extent. Second, the fact that we require lagged returns of up to 120 months also limits the number of observations in each industry subset. Consequently, the results of the following regression might not be robust and must be evaluated with caution.

Table 3 **Firm-Month Observations across Industries**

Table 3 shows the number of firm month observations per lag across samples and industries.

Panel A. Germany and Sweden

Lag	Industry 1	Industry 2	Industry 3	Industry 4	Industry 5	Industry 6	Industry 7	Industry 8
1	11,262	18,128	64,815	59,496	20,886	44,521	53,559	12,916
12	10,279	16,745	59,865	54,920	18,999	40,539	48,870	11,801
24	9,223	15,324	54,688	50,069	16,956	36,437	43,818	10,646
36	8,197	13,935	49,663	45,409	15,000	32,572	38,930	9,579
48	7,256	12,592	44,870	40,979	13,177	28,987	34,353	8,568
60	6,364	11,324	40,289	36,847	11,494	25,661	30,018	7,594
72	5,526	10,145	36,036	33,027	10,015	22,650	26,017	6,684
84	4,758	9,009	32,024	29,441	8,665	19,859	22,335	5,827
96	4,049	7,995	28,328	26,049	7,404	17,207	18,980	5,036
108	3,463	7,103	25,017	22,871	6,250	14,905	15,949	4,342
120	3,004	6,394	22,076	20,027	5,266	12,930	13,230	3,770

Panel B. Germany

Lag	Industry 1	Industry 2	Industry 3	Industry 4	Industry 5	Industry 6	Industry 7	Industry 8
1	8,513	12,693	45,360	47,834	13,154	34,921	38,443	10,058
12	7,838	11,832	42,128	44,455	12,203	31,825	35,289	9,229
24	7,118	10,968	38,780	40,902	11,174	28,644	31,897	8,386
36	6,410	10,123	35,494	37,451	10,162	25,663	28,571	7,603
48	5,763	9,277	32,317	34,119	9,175	22,864	25,397	6,858
60	5,145	8,491	29,246	30,984	8,224	20,244	22,351	6,135
72	4,553	7,743	26,342	28,031	7,333	17,852	19,470	5,441
84	4,006	7,020	23,545	25,253	6,479	15,607	16,773	4,772
96	3,489	6,347	20,909	22,596	5,637	13,473	14,254	4,142
108	3,055	5,716	18,515	20,050	4,834	11,641	11,936	3,598
120	2,702	5,189	16,360	17,658	4,108	10,070	9,859	3,159

Panel C. Sweden

1	2,749	5,435	19,455	11,662	7,732	9,600	15,116	2,858
12	2,441	4,913	17,737	10,465	6,796	8,714	13,581	2,572
24	2,105	4,356	15,908	9,167	5,782	7,793	11,921	2,260
36	1,787	3,812	14,169	7,958	4,838	6,909	10,359	1,976
48	1,493	3,315	12,553	6,860	4,002	6,123	8,956	1,710
60	1,219	2,833	11,043	5,863	3,270	5,417	7,667	1,459
72	973	2,402	9,694	4,996	2,682	4,798	6,547	1,243
84	752	1,989	8,479	4,188	2,186	4,252	5,562	1,055
96	560	1,648	7,419	3,453	1,767	3,734	4,726	894
108	408	1,387	6,502	2,821	1,416	3,264	4,013	744
120	302	1,205	5,716	2,369	1,158	2,860	3,371	611

Coefficient estimates and their t-statistics are reported in detail in Appendix A, Table XII-XVII, and the graphs plotting the estimates in Appendix B, Figure IV-IX.

Examining the short-term reversal, we find that the coefficient estimate for the one month lagged return is negative and statistically significant across most industries. The combined sample shows this short-term reversal effect significantly in every industry apart from industry 1 (Energy & Utilities), which clearly has the lowest number of observations at lag 1 (c.11,000). Germany misses the effect additionally for industry 7 and 8. While this is not surprising for industry 8 (Real Estate), as the number of observations is certainly small (c.10,000), it is surprising for industry 7 (IT & Telecommunications), which, in Germany, has the third highest number of observations (c.38,000) at lag 1. In Sweden, the short-term reversal is surprisingly persistent: while for lag 1 the average number of observations is below 10,000, the short term-reversal effect can be observed at four of the eight industries. What is most striking here, is that industry 2 (Materials) with less than 5,500 observations shows a significantly negative first-order estimate, while again industry 7 (IT & Telecommunications) with more than 15,000 observations shows none. This is consistent with the combined sample and with Germany, where the third smallest industry 2 (Materials) already shows a significant short-term reversal effect, while the third biggest industry 7 (IT & Telecommunications) only shows this effect in the combined sample.

Assessing the momentum effect, we find that most industries do not show any significant effect. This can be attributed to the fact that most sets contain only a low number of observations which considerably impacts the significance of such an effect. However, some observations are noteworthy: industry 8 (Real Estate) and industry 2 (Materials) show a momentum effect only in Sweden, with three and two significantly positive estimates between lag 2 and 11 respectively, even though the Swedish sample is considerably smaller than the German and the combined one. Germany, on the other hand, is the only country with a momentum effect in industry 1 (Energy & Utilities), which again is surprising as this is the industry with the least observations. However, the effect here is still limited to two significantly positive estimates between lag 2 and 11. Only industry 3 (Industrials) shows some momentum effect across all samples, with two significantly positive estimates each. In the combined sample, we additionally find the effect in industry 4 (Consumer) and industry 7 (IT & Telecommunication) with three significantly positive estimates each, while in both these industries the effect cannot be observed in Germany or Sweden alone.

When we look at the coefficient estimates at annual lags, we cannot identify significant annual patterns: in the combined sample, we find that out of the 80 (ten annual estimates for each industry) only 13 are significantly positive. Moreover, a large number of annual coefficients is close to zero or even negative. Industry 3 (Industrials) is the only industry showing a weak annual pattern across all samples with three significantly positive estimates in the combined sample (at lags 12, 36, and 108), two in Germany (at lags 12 and 108), and four in Sweden (at lags 12, 24, 36, and 120). However, it has to be noted that this industry is the biggest in the combined sample, the second biggest in Germany, and the biggest in Sweden. Nonetheless, it is remarkable to find a pattern in Sweden, while this set has an average of only c.11,500 firm-month observations across all lags. This makes it the smallest set with more than three significantly positive annual estimates, among all sets assessed in this paper. The only other industry that somehow shows a pattern is industry 4 (Consumer), again one of the biggest industries across all samples. Here, we find a weak pattern in the combined sample with three significantly positive estimates. However, the pattern is considerably weaker in Germany and Sweden (only one and two significantly positive annual estimates, respectively). Interestingly, industry 7 (IT & Telecommunication), which is the second biggest in Sweden, and the third biggest in Germany and in the combined sample, shows no annual seasonality pattern. This industry also did not show any short-term reversal or momentum effect in Germany and in Sweden.

The absence of return seasonalities in nearly all industries can be linked to the fact that the companies in the different industries are too similar. This leads to a similar exposure to the same risk factors, and in turn to a low variance of firm factor loadings in the cross-section. Consistent with this explanation is previous work by Fama & French (1997) and Keloharju et al. (2016), according to which industries can be interpreted as risk factors themselves. However, we identify two exceptions from the general absence of patterns: (1) Industry 3 (Industrials) shows a higher seasonality pattern than other industries, and (2) Industry 7 (IT & Telecommunications) shows a weaker seasonality pattern. One could conclude that a more traditional industry, such as Industrials, shows more seasonalities than a more modern high-tech industry, such as IT & Telecommunications. Moreover, we once again observe that seasonalities are generally stronger in Sweden than in Germany, as we can find them even in the small set of industry 3 (Industrials).

6 Robustness of Regression Results

6.1 Univariate Regressions excluding January

It is documented in the academic financial literature that January usually shows higher returns of anomalies compared to every other month: As Jegadeesh & Titman (2011) point out, many of the known strategies such as return reversals, the size effect and the book-to-market effect are significantly stronger in January. We conduct the same regressions as before, but now we exclude all January observations. This is to rule out the possibility that seasonalities arise from seasonal variation in January returns only. Coefficient estimates are plotted in Figure 6, and reported in Appendix A, Table XVIII, together with their t-statistics.

The results suggest that stocks in all three samples (both countries combined, Germany, Sweden) exhibit a short-term reversal effect even if January observations are excluded, because coefficients for lag 1 are negative and statistically significant. However, this effect is slightly smaller in magnitude for each sample when January is excluded (compare Appendix A, Table I and XVIII). The momentum effect also holds when January returns are excluded. Interestingly, in contrast to the weaker short-term reversal effect, the momentum effect is somehow stronger with one more significantly positive estimate between lag 2 and 11 for each sample (five compared to four in the combined sample, four compared to three in Germany, and seven compared to six in Sweden). This is consistent with Jegadeesh & Titman (1993), who document negative momentum strategy returns in January. However, overall the changes in both effects are rather small.

In the combined sample, the annual pattern holds when January observations are excluded. As with January, nine of the ten annual estimates are positive (all apart from the one at lag 120, which is slightly negative), and the pattern is very similar to the one with all months (see Figure 6, Panel A). However, now we only find five annual estimates to be significant (at lags 12, 24, 72, 84, and 108), compared to seven before. More precisely, the estimates at lags 36 and 48 are not significantly positive anymore – these estimates are also the ones with the lowest significance in the sample with all months (90% and 95%, respectively). Estimates at lags 72 and 84 also lose some of their significance, as they are now significant at the 95% level only, compared to the 99% level before.

In Germany, we find the same trend, however, it has bigger implications: While the pattern is similar to the one in the sample with all months (see Figure 6, Panel B), now only three of the ten annual estimates are significantly positive (at lags 12, 24, and 108), compared to five in the sample with all observations. In particular, the estimates at lags 72 and 84 are not significant anymore, thus seriously limiting the significance of the annual pattern in Germany.

In Sweden, on the other hand, the pattern is least affected. We still find seven annual estimates to be significantly positive (at lags 12, 24, 36, 48, 60, 72, and 108), compared to eight before: only the estimate at lag 120, which was significant at the 90% level only, loses its significance when excluding January observations. Interestingly, some of the other significant annual estimates even increase their significance, showing higher t-statistics (at lags 48, 60, 72, and 108). The fact that the Swedish sample without January almost shows no difference is also confirmed by Figure 6, Panel C, where we still find the strongest annual pattern.

To test if the differences in annual patterns can be attributed to the month of January, we also exclude observations from every other month and compare the results to the ones when excluding observations from January (see Appendix A, Table XIX). We find that excluding observations of other months shows no difference in the significance of annual patterns for most of the months. This proves true across all samples. Thus, we conclude that the weaker annual patterns in the combined sample and in Germany can indeed be attributed to the January effect. In Sweden, however, where the pattern is strongest even before excluding January observations, the pattern is robust and excluding January observations does not have any impact.

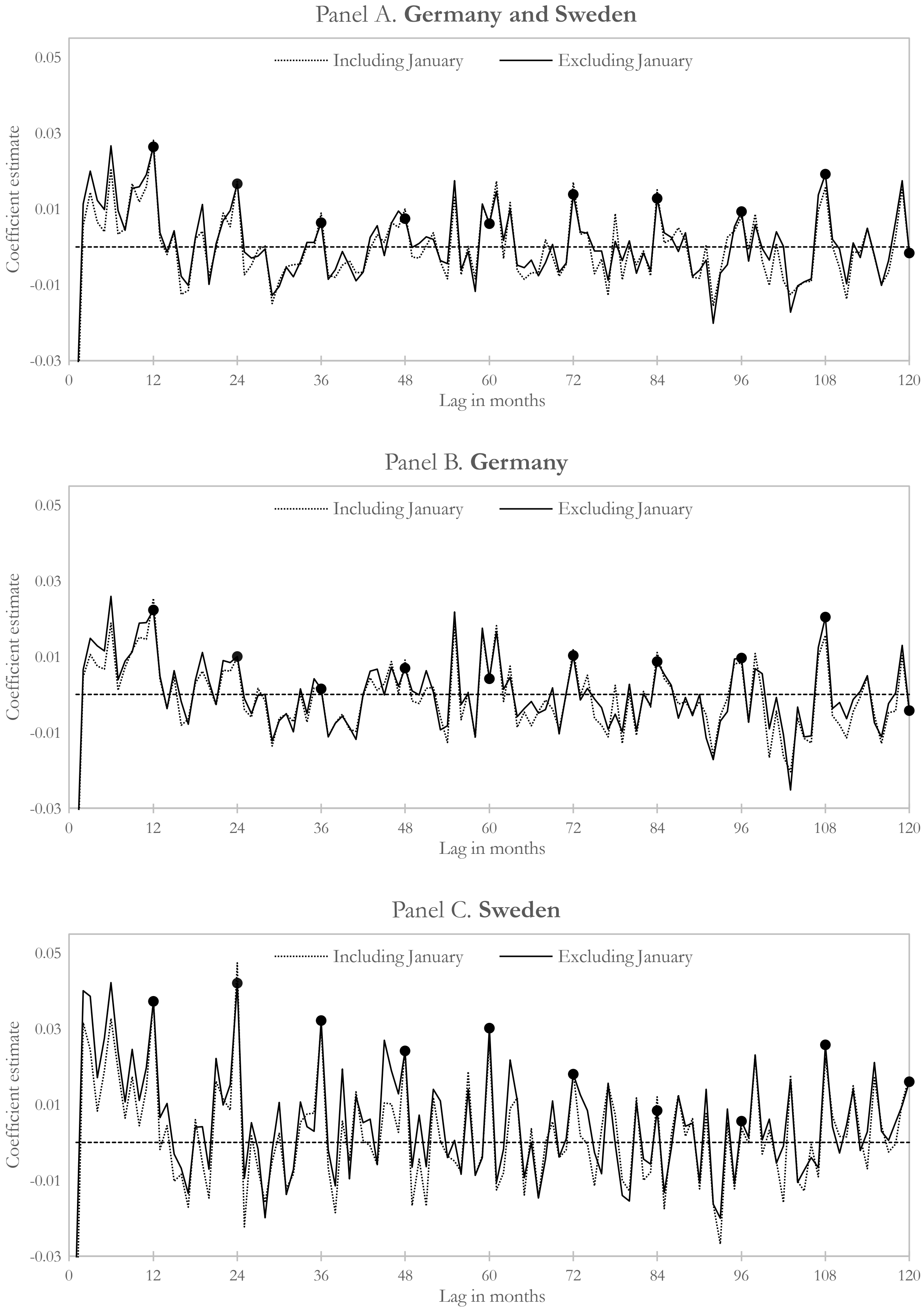


Figure 6. Cross-sectional regressions of monthly returns. Monthly univariate Fama MacBeth (1973) regressions of the form $r_{i,t} = a_{k,t} + b_{k,t}r_{i,t-k} + e_{i,t}$, are calculated for each month *t* and lag *k*, and where $r_{i,t}$ is the return of stock *i* in month *t*. The lagged variable $r_{i,t-k}$ is the return of stock *i* in month *t-k*. The regression is calculated for every month *t* from February 1986 through December 2015 (359 months), and for lag k values $1-120$. Figure 6 plots the time series averages of $b_{k,t}$, including and excluding January observations (dotted and solid line, respectively). The analysis includes listed common stocks from Germany and Sweden (Panel A), Germany only (Panel B), and Sweden only (Panel C).

6.2 Regression Results for the First and the Second Half of the Sample

Another robustness check is splitting the three samples into two different time periods and running the regressions again on these six sets separately. We do this in order to determine whether the seasonality effect is persistent over time. Following Keloharju et al. (2016), and Fama & French (1992), we split the samples in two equally sized time periods, the first half ranging from January 1986 to December 2000 and the second half from January 2001 to December 2015. Note that the second half includes three financial crises, e.g. the aftermath of the dot com bubble burst in late 2000, the 2007-08 financial crisis and the following sovereign debt crisis in Europe. This might not only affect the seasonality pattern in general but also the potential difference between the countries. We are also aware of the fact that splitting a 30-year panel into two 15-year panels reduces statistical significance since the number of firm-month observations drops noticeably. The regression results are reported in Appendix A, Table XX and XXI.

When we split the three samples in two sets each, we find that the short-term reversal and the momentum effect are robust across almost all samples. However, in the combined sample, the negative estimate at lag 1 is less significant in the first than in the whole time period, and even insignificant in Germany. In the second time period, on the other hand, it is not only stronger in magnitude but also more significant. In Sweden, the short-term reversal is rather similar across both time periods, and only slightly less significant than in the full sample. The momentum effect is observable across all samples and time periods. The combined sample shows the same number of four significantly positive estimates between lag 2 and 11 in the whole time period, and in each the first and second half. In Germany, the significance of the effect is similar across the whole time period and the first half, but decreases in the second. In Sweden, on the other hand, the significance decreases in the first half, while in the second half it remains similar to the whole time period.[9]

Assessing annual patterns, we first compare the first half with the whole time period. The combined and the German sample show higher coefficient estimates at annual lags in the first half, while this cannot be observed in Sweden. Due to the smaller sample sizes, the number of significant annual estimates decreases across all samples. The combined sample shows four significantly positive annual estimates in the first half (at lags 12, 24, 72, and 84). The annual estimates with the lowest significance in the overall sample are not significant anymore, i.e. the estimates at lags 36, 48, and 108. While this limits the significance, the annual pattern still seems stronger due to the higher absolute values of annual coefficients (see Figure 7, Panel A-I). Germany shows a similar effect: the pattern is also stronger in the first half, and the absolute value of nine out of the ten

[9] Germany shows three significantly positive estimates between lag 2 and 11 in the whole time period, three in the first time period, and one in the second. Sweden shows six in the whole time period, three in the first half, and five in the second half (compare Appendix A, Table I, XX and XXI).

annual estimates increases (see Figure 7, Panel B-I). The number of significantly positive annual coefficients, however, decreases to three (at lags 12, 72, and 84) compared to five in the sample with the whole time period. Sweden, on the contrary, shows a weaker annual pattern in both the level of coefficients and the number of significant coefficients (see Figure 7, Panel C-I). The pattern is additionally limited to the first five years, where three annual estimates are significantly positive (at lags 12, 24, and 60). After lag 60, there is only one significant peak at lag 108, and even negative estimates at lags 84 and 96 (however, insignificant).

Comparing the second half with the whole time period, we find that the pattern clearly weakens in the combined sample and in Germany, while it strengthens in Sweden. The combined sample now only shows three significantly positive estimates (at lags 12, 24, and 36). We additionally find a significantly negative estimate at lag 60, thus effectively eliminating a significant annual pattern after lag 36 (see Figure 7, Panel A-II). In Germany, we cannot identify an annual pattern at all: there is only one significantly positive estimate at lag 12, a significantly negative estimate at lag 60, and many disruptions (see Figure 7, Panel B-II). Additionally, in both the combined sample and the German sample the value of most annual coefficients decreases compared to the whole time period. In contrast, Sweden shows a very strong pattern in the second half with eight significantly positive estimates (at lags 12, 24, 36, 48, 60, 84, 96, and 108). Compared to Sweden's whole sample, the pattern is stronger at longer lags: estimates at lags 84 and 96 are not only higher than before but now also statistically significant. While the estimates at lags 72 and 120 lose their significance, they are still clearly identifiable as peaks (see Figure 7, Panel C-II).

The fact that seasonality patterns rather become weaker with smaller samples relates to Keloharju et al. (2016), who suggest that seasonality patterns are stronger for samples that are exposed to a higher number of risk factors and show higher variance of risk factor loadings. However, it is worth noting that in Germany the pattern in the second half of the period is unnoticeable, which could relate to the fact that German stocks had a higher exposure to the various crises that occurred during that time. The difference in seasonality patterns between German and Swedish stocks might also be due to the fact that the Swedish market is not fully integrated into the Eurozone. Consequently, German and Swedish stocks are exposed to different risk factors which exhibit different seasonal variations. Nonetheless, the absence of an annual pattern is surprising, because this set includes more observations (an average of 84,968 per lag, and 1,382 unique firms) than the period from 1986 to 2000 (27,573 with 885 unique firms). This should lead to more variance in risk factor exposure, what in turn should induce higher seasonal variation in stock returns. We can only contemplate that the various crises during this period led to distorted risk factor premiums and in this way to "abnormal" stock returns. Similarly, Daniel & Moskowitz (2011), report that returns of the momentum strategy reverse in times of high market volatility.

Overall, the pattern seems to be robust in the combined sample and in Sweden, but less robust in Germany, where the seasonalities are not as strong in general. Additionally, while the combined sample and Germany show a stronger pattern in the first time period, Sweden shows a stronger pattern in the second.

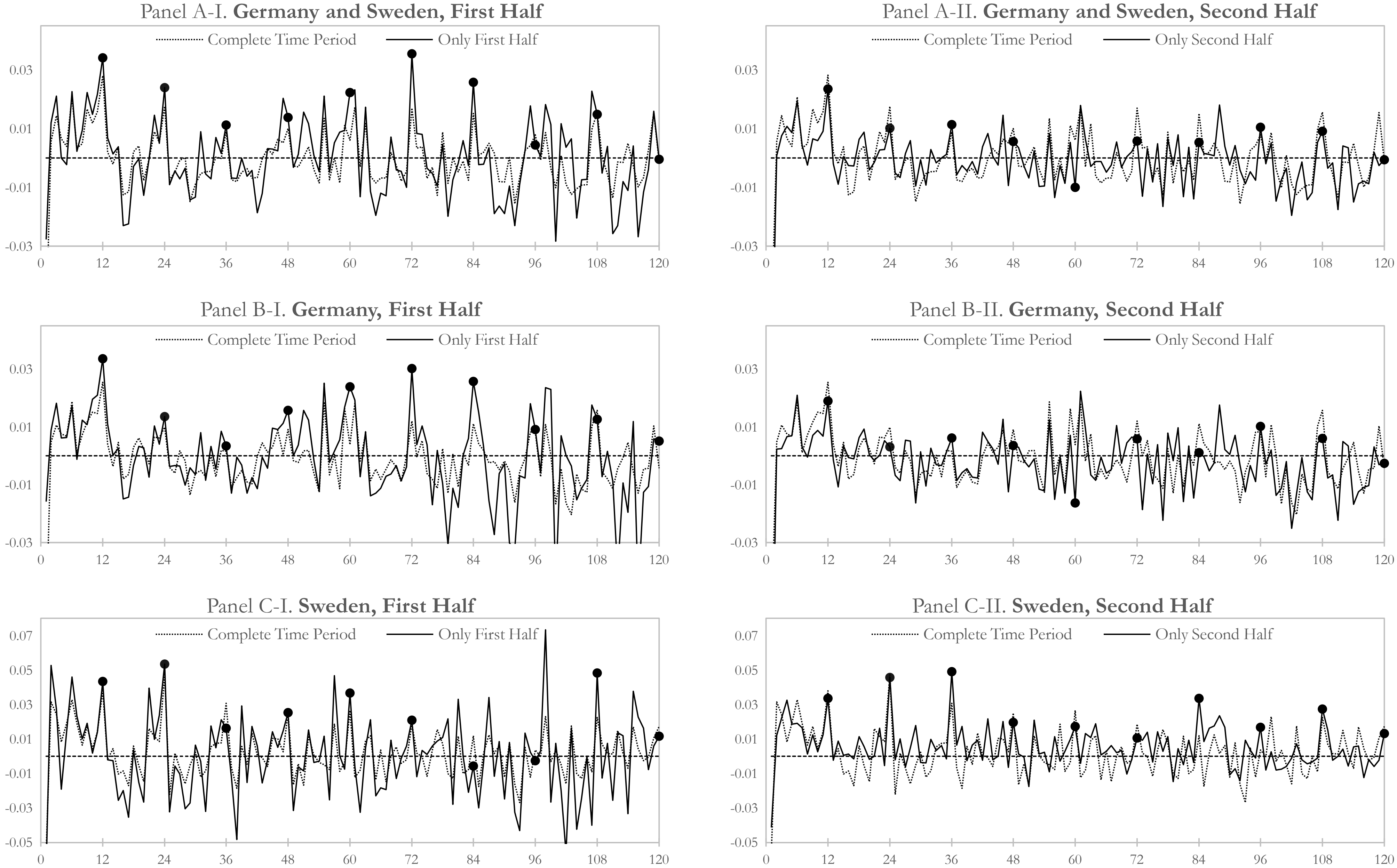


Figure 7. Cross-sectional regressions of monthly returns Monthly univariate Fama MacBeth (1973) regressions of the form $r_{i,t} = a_{k,t} + b_{k,t} r_{i,t-k} + e_{i,t}$, are calculated for each month *t* and lag *k*, and where $r_{i,t}$ is the retu of stock *i* in month *t*. The lagged variable $r_{i,t-k}$ is the return of stock *i* in month *t-k*. The regression is calculated for every month *t*, and for lag *k* values 1 – 120. For the "Complete Time Period" the regression is calculat from February 1986 through December 2015 (359 months), for "Only First Half" from February 1986 through December 2000 (179 months), and for "Only Second Half" from February 2001 through December 2015 (1 months). Figure 7 plots the time series averages of $b_{k,t}$. The analysis includes listed common stocks from Germany and Sweden (Panel A-I and A-II), Germany only (Panel B-I and B-II), and Sweden only (Panel C-I and II). The X-axis always shows the lags in months, and the Y-axis the magnitude of the coefficient estimates.

6.3 Multiple Regressions

Following Jegadeesh (1990) we also perform cross-sectional multiple regressions to ensure the robustness of our approach. In this regression setup, coefficient estimates for multiple historical lags are estimated at the same time. We specify three different regression models where the following lags are estimated jointly: (1) lags 1 to 12, lag 24 and lag 36, (2) lags 1 to 12, lag 24, lag 36, lag 48 and lag 60 and (3) lags 1 to 12, lag 24, lag 36, lag 48, lag 60, lag 72, lag 84, lag 96, lag 108 and lag 120. Heston & Sadka (2008) include even higher annual lags as part of the seasonality pattern. They find that almost all annual coefficient estimates for the first ten years are statistically positive, independent from using simple or multiple regressions.

Table 4 displays results of the multiple regressions in comparison to the results of the univariate regressions. Examining the short-term reversal effect, we find it to be clearly robust across all samples. Compared to the univariate regression with all firms, the effect is clearly stronger in the combined sample and in Germany, both in magnitude and significance. This is true for all specifications, and strongest for specification (3). In Sweden, however, we find that the short-term reversal effect is now smaller than before. While it is still significant on a 99% level in both specification (1) and (2), the effect loses its significance in specification (3).

The momentum effect is observable in the combined sample and in Germany, independent from the regression method. However, we find that the start of the effect is delayed, as the estimate at lag 2 is often still negative (however, mostly insignificant) and only changes to positive afterwards. This is still consistent with Jegadeesh & Titman (1993), who find a positive correlation between this month's performance of one stock with the performance in the preceding three- to 12-month period. The momentum effect is strongest in specification (1) and then decreases as more lags are included in the regression. This leads to a different magnitude of the effect when comparing it to the univariate regressions, e.g. in the combined sample the multiple regressions show a higher number of significantly positive estimates between lag 2 and 11 for specification (1) and (2), but a lower number for specification (3). In Germany, we additionally find the negative estimate at lag 2 to be significant in (2). Overall, apart from the delayed start, the momentum effect is robust in the combined sample and in Germany. In Sweden, however, where we see the strongest momentum effect using a univariate regression, we now do not see a significant momentum effect in any of the specifications. Specification (1) shows only two significantly positive estimates between lag 2 and 11, (2) none, and (3) only one. Interestingly, we do not see a difference in the estimate at lag 2 in Sweden; it stays positive across all specifications and is even significant in specification (3).

When we look at annual estimates, we find that multiple regressions produce a lower number of significantly positive estimates across all samples, especially when more variables are included. The combined sample shows only two significantly positive annual estimates instead of three in specification (1), three instead of four in specification (2) and four instead of seven in specification (3) (see Table 4, Panel A). Some lags have a stronger estimate with higher significance, i.e. lag 48 in specification (2) and lag 96 in specification (3), but the overall trend to less significant estimates clearly remains. Germany shows one significantly positive annual estimate instead of two in in specification (1), two as before in specification (2) and four instead of five in specification (3) (see Table 4, Panel B). Interestingly, similar to the combined sample, the estimates in specification (2) at lag 48 and in specification (3) at lag 48 and lag 96 increase in both magnitude and significance. However, the overall trend of a decreasing number of significant estimates also remains in Germany. In Sweden, we find an even more unfavorable difference to the univariate regressions. While specification (1) shows the same amount of three significantly positive annual estimates, (2) now shows two instead of five, and (3) only one instead of eight (see Table 4, Panel C). We once again clearly see that the multiple regression with the most independent variables shows the highest effect on seasonalities and in Sweden completely eliminates all return patterns (short-term reversal, momentum, annual seasonality effect).

Overall, we find that results are rather robust when using specification (1) and (2), even Sweden shows very similar results in specification (1). However, when including more historical returns in the same regression, the significance of estimates decreases significantly, and thus we do not find a significant annual pattern in any of the samples with specification (3). This is somehow consistent with Heston & Sadka (2008), who also see a decline in significance and magnitude of their estimates. However, where Heston & Sadka (2008) still find relatively high t-statistics for high annual lags in their multiple regression, we do not. One reason for that could be the limited sample sizes – we cover less than half the time horizon compared to Heston & Sadka (2008). This is supported by the fact that the smallest sample, Sweden, shows the strongest decrease in the magnitude of seasonality patterns.

Table 4 **Multiple cross-sectional Regressions of Returns**

Table 4 displays the univariate regression results from all firms as comparison and the monthly multiple cross-sectional regressions from this section, where all past lags are included at once. The multiple regressions are calculated for each month *t* and lag *k* in the cross-section, where $r_{i,t}$ is the return of stock *i* in month *t*. The lagged variable $r_{i,t-k}$ is the return of stock *i* in month *t-k*. The regression is calculated for every month *t* from February 1986 through December 2015 (359 months), and for lag *k* values 1 - 120 (coefficient estimates are reported for lags 1-12 and every 12th lag afterwards). Regression results are reported separately for different regression specifications: (1) including lags 1-12, 24 and 36, (2) including lags 1-12, 24, 36, 48 and 60 and (3) including lags 1-12 and every annual lag thereafter. The time series averages of the coefficient estimates from the cross-sectional regressions as well as t-statistics are reported. The reported Fama MacBeth (1973) t-statistics are corrected for heteroscedasticity and autocorrelation using Newey West (1987) correction with 12 lags (*** p<0.01, ** p<0.05, * p<0.1). The analysis includes listed common stocks from Germany and Sweden (Panel A), Germany only (Panel B), and Sweden only (Panel C).

Panel A. Germany and Sweden

	Univariate Regression		Specification (1)		Specification (2)		Specification (3)	
Lag	Estimate	t-Stat.	Estimate	t-Stat.	Estimate	t-Stat.	Estimate	t-Stat.
1	-0.0572***	(-5.591)	-0.0757***	(-8.230)	-0.0785***	(-7.876)	-0.0878***	(-6.052)
2	0.00561	(0.887)	-0.00501	(-0.708)	-0.00433	(-0.734)	-0.0102	(-1.217)
3	0.0144**	(2.010)	0.00930*	(1.731)	0.0108*	(1.716)	0.00167	(0.179)
4	0.00657	(0.983)	0.00117	(0.214)	0.00250	(0.404)	-0.00395	(-0.434)
5	0.00393	(0.537)	0.00688	(1.152)	0.00765	(1.230)	0.000954	(0.163)
6	0.0207***	(3.092)	0.0173***	(2.921)	0.0201***	(2.783)	0.0177***	(2.800)
7	0.00330	(0.683)	0.00789*	(1.694)	0.00507	(0.928)	0.00868	(1.209)
8	0.00481	(0.899)	0.00436	(0.866)	0.00852*	(1.916)	0.0232***	(3.007)
9	0.0167**	(2.536)	0.0170***	(3.205)	0.0124**	(2.216)	0.0107	(1.246)
10	0.0118	(1.599)	0.0111*	(1.764)	0.000142	(0.0193)	0.00376	(0.330)
11	0.0158**	(2.566)	0.0164**	(2.567)	0.0150**	(2.204)	0.0222**	(2.564)
12	0.0281***	(4.577)	0.0315***	(4.127)	0.0199***	(3.394)	0.0261***	(4.405)
24	0.0176***	(3.773)	0.0103**	(2.317)	0.00541	(1.062)	0.00111	(0.149)
36	0.00891*	(1.749)	0.00678	(1.271)	0.00962*	(1.663)	0.0101	(1.359)
48	0.00997**	(2.046)			0.0116***	(2.658)	0.0109*	(1.679)
60	0.00601	(0.851)			0.00672	(1.022)	0.0108	(1.478)
72	0.0170***	(2.818)					0.00976	(1.100)
84	0.0151***	(3.136)					0.00123	(0.252)
96	0.00791	(1.176)					0.0118*	(1.757)
108	0.0156***	(2.822)					0.0147**	(2.315)
120	-0.00118	(-0.182)					-0.00717	(-1.253)

Panel B. Germany

	Univariate Regression		Specification (1)		Specification (2)		Specification (3)	
Lag	Estimate	t-Stat.	Estimate	t-Stat.	Estimate	t-Stat.	Estimate	t-Stat.
1	-0.0571***	(-4.797)	-0.0822***	(-8.284)	-0.0842***	(-7.421)	-0.0951***	(-5.934)
2	0.00472	(0.788)	-0.00768	(-1.178)	-0.0113**	(-2.139)	-0.0108	(-1.179)
3	0.0106	(1.538)	0.00495	(0.765)	0.00522	(0.817)	-0.00151	(-0.150)
4	0.00751	(1.177)	0.00161	(0.259)	0.00343	(0.486)	-0.00640	(-0.577)
5	0.00674	(0.954)	0.00476	(0.665)	0.00979	(1.491)	0.00170	(0.255)
6	0.0188***	(2.679)	0.0184**	(2.586)	0.0191**	(2.045)	0.0187***	(2.954)
7	0.00108	(0.235)	0.00595	(1.401)	0.00313	(0.563)	0.00781	(1.001)
8	0.00728	(1.362)	0.00492	(0.892)	0.0110**	(2.056)	0.0265***	(2.947)
9	0.0117	(1.462)	0.0170**	(2.473)	0.0131**	(2.160)	0.0166*	(1.868)
10	0.0151**	(2.388)	0.0132**	(2.149)	0.000599	(0.0887)	0.00530	(0.435)
11	0.0146**	(2.348)	0.0154**	(2.427)	0.0148**	(1.993)	0.0235**	(2.243)
12	0.0254***	(3.827)	0.0296***	(4.033)	0.0212***	(4.379)	0.0263***	(3.881)
24	0.00985**	(1.987)	0.00346	(0.712)	-0.000457	(-0.0802)	-0.000528	(-0.0682)
36	0.00162	(0.291)	0.00103	(0.184)	0.00773	(1.329)	0.00804	(0.915)
48	0.00913	(1.423)			0.0117**	(2.542)	0.0125*	(1.729)
60	0.00390	(0.450)			0.00297	(0.395)	0.0119	(1.428)
72	0.0120*	(1.846)					0.0104	(0.923)
84	0.0111**	(2.023)					0.000794	(0.147)
96	0.00826	(1.095)					0.0137*	(1.752)
108	0.0157**	(2.497)					0.0199**	(2.527)
120	-0.00437	(-0.624)					-0.0140*	(-1.934)

Panel C. Sweden

	Univariate Regression		Specification (1)		Specification (2)		Specification (3)	
Lag	Estimate	t-Stat.	Estimate	t-Stat.	Estimate	t-Stat.	Estimate	t-Stat.
1	-0.0552***	(-4.448)	-0.0479***	(-4.647)	-0.0388***	(-3.060)	-0.0710	(-1.085)
2	0.0316**	(2.457)	0.0238	(1.296)	0.0285	(1.383)	0.117*	(1.692)
3	0.0244***	(2.702)	0.0282**	(2.573)	0.0234	(1.400)	0.0504	(1.106)
4	0.00824	(0.723)	-0.00629	(-0.470)	-0.00132	(-0.0996)	0.0288	(0.803)
5	0.0190*	(1.826)	0.0169	(1.089)	-0.000107	(-0.00730)	-0.0428	(-0.828)
6	0.0327***	(3.303)	0.0390**	(2.265)	-0.0116	(-0.570)	-0.0706	(-0.771)
7	0.0192**	(2.246)	0.0193	(1.228)	0.0119	(0.970)	0.0294	(0.630)
8	0.00640	(0.919)	-0.00156	(-0.149)	-0.00332	(-0.270)	0.0450	(0.628)
9	0.0173**	(1.992)	0.00421	(0.403)	-0.0218	(-1.029)	-0.0261	(-0.606)
10	0.00441	(0.416)	0.0110	(0.741)	-0.0157	(-0.850)	-0.0765	(-1.326)
11	0.0142	(1.377)	0.00510	(0.424)	0.00547	(0.352)	-0.0980	(-1.066)
12	0.0379***	(4.392)	0.0302***	(2.779)	0.0138	(0.967)	0.0791*	(1.780)
24	0.0474***	(5.825)	0.0371***	(4.799)	0.0411***	(3.659)	0.0417	(1.280)
36	0.0307**	(2.519)	0.0241**	(2.349)	0.0111	(0.679)	0.0410	(0.768)
48	0.0251*	(1.669)			0.00552	(0.384)	0.0786	(0.679)
60	0.0266***	(3.024)			0.0414***	(3.089)	-0.0208	(-0.387)
72	0.0186*	(1.790)					-0.0133	(-0.419)
84	0.0120	(1.187)					0.0206	(0.380)
96	0.00355	(0.361)					0.00370	(0.116)
108	0.0224*	(1.936)					-0.0530	(-1.254)
120	0.0172*	(1.866)					-0.0410	(-0.916)

7 Trading Strategies based on Seasonality Patterns

Many trading strategies in the academic literature are based on observed patterns in historical returns, e.g. Jegadeesh & Titman (1993, 2001), Moskowitz & Grinblatt (1999), and De Bondt & Thaler (1985, 1987). More recent research shows the profitability of seasonality trading strategies (Heston & Sadka, 2008, 2010; Keloharju et al., 2016).

Similarly, we want to construct a long-short trading strategy that tries to exploit the previously reported annual seasonality pattern in stock returns. In doing so, the economic significance of the return seasonalities can be evaluated. Following the methodology of Jegadeesh & Titman (1993), stocks are sorted into decile portfolios of equal size. The return of a specific long-short trading strategy then simply is the spread between the top and the bottom decile portfolio. This approach limits the problems arising from our short sample and the cross-sectional regression approach: First, not every coefficient estimate for every lag can be expected to be significant. Second, cross-sectional regressions do not take into account the whole variation in security returns available. Since past returns at annual lags show considerable predictive power of current returns, the strategy buys (sells) stocks that were winners (losers) during months at annual lags. Subsequently, this strategy is referred to as "Annual strategy". To identify the long and short leg of the annual strategy, at the beginning of every month, stocks are ranked based on their average returns across annual lags. Stocks are then assigned to ten portfolios of equal size, where the top portfolio contains the stocks with the highest ranks (highest historical average returns), and the bottom portfolio the ones with the lowest ranks. The top and the bottom portfolio contain the same number of stocks and weight stocks equally. This long-short portfolio is held through the month and rebalanced thereafter.

In order to assess the performance of the Annual strategy, we compare it to the returns of two other long-short strategies, namely a "Nonannual" strategy and an "All Months" strategy. The difference between those strategies lies in the monthly ranking of stocks: the All Months strategy considers average returns over all months in the formation period, whereas the Nonannual strategy excludes monthly returns at annual lags from the average return calculation. Additionally, we construct a "Difference" strategy, which is long in the "Annual" and short in the "Nonannual" strategy.

The decile portfolios of all trading strategies are constructed based on historical returns during a formation period. Initially, three different formation periods are considered: (1) the past 1-year period, (2) the past 2-5 year period, and (3) the past 6-10 year period[10]. The ranking periods (1) and

[10] For example, the 6-10 year Annual strategy ranks stocks based on their average return across lags 72, 84, 96, 108 and 120. The All Months strategy for this formation interval uses averages return over lags 61-120, whereas the Nonannual strategy uses returns over lags 61-120, excluding lags 72, 84, 96, 108 and 120.

(2) are selected in a way, such that the one year Jegadeesh & Titman (1993) momentum, and the 2-5 year De Bondt & Thaler (1985, 1987) reversal horizon are not mixed. The long formation horizon of (3) aims at examining the persistence of seasonalities (Heston and Sadka, 2008). Later, we construct strategies based on formation periods which take into account the specific findings in our samples.

To counterbalance selection bias, we include delisting returns in our sample. However, since Compustat does not provide delisting returns directly, we impute a delisting return of minus 30% as a proxy, thereby following Keloharju et al. (2016)[11]. We impose the additional condition, that there must be at least 30 different stocks available (at least three stocks per decile portfolio) in a month for a long-short strategy to be constructed.

Based on our previous findings, we would expect that the annual strategies perform better in a sample, where coefficient estimates at annual lags are high and statistically significant. In our case that would mean that the strategy performs well in the Swedish sample, while performing better in the second as opposed to the first half of this sample. In contrast to that, for German stocks we expect the strategy to work better in the first half than in the second one, since the seasonality pattern is more pronounced there. Similarly, when implementing the strategy in the combined German and Swedish sample, the strategy should perform better in the first than in the second half (compare to section 5.2).

7.1 Performance of Trading Strategies

Table 5 to Table 7 report the average monthly returns (using simple means) of the strategies (Annual, Nonannual, Difference, All Months) for each sample, various formation periods (Panels A to C), and three different subperiods. Furthermore, we test if the mean returns of the top decile portfolio and bottom decile portfolio are significantly different from each other, using two-sample t-tests.[12] The t-statistics of those tests are shown in parenthesis.

[11] We obtain similar results using delisting returns of minus 100%.

[12] For the Difference strategy, we test if the mean returns of the Annual strategy and Nonannual strategy are significantly different using Satterthwaite's approximation of the t-test.

Table 5 **Average Monthly Returns of Trading Strategies based on Past Returns in Germany and Sweden**

Table 5 reports simple average monthly returns (in percent) of four different long-short trading strategies (Annual, Nonannual, Difference and All Months). The performance is reported for the whole sample (January 1987 to December 2015), for the first half of the sample (January 1987 to December 2000) and for the second half (January 2002 to December 2015). Every month stocks are assigned into decile portfolios of equal size, based on their historical average returns according to various categories. Within a decile portfolio stocks are equally weighted. The return of a strategy is the return on the top decile portfolio minus the return on the bottom decile portfolio. Corresponding t-statistics are reported in parenthesis. Panels A to C report the performances of the strategies for different formation intervals.

Panel A. Year 1

Strategy	Whole sample	First half of the sample	Second half of the sample
Annual	0.33	1.26	-0.59
	(0.34)	(2.09)	(-0.32)
Nonannual	-3.31	0.47	-7.38
	(-3.16)	(0.69)	(-3.79)
Difference	3.64	0.79	6.79
	(2.83)	(1.37)	(2.70)
All Months	-3.02	1.03	-7.53
	(-2.85)	(1.54)	(-3.81)

Panel B. Year 2-5

Annual	0.38	0.77	-0.12
	(0.59)	(1.33)	(-0.09)
Nonannual	-1.11	0.13	-1.77
	(-1.60)	(0.20)	(-1.25)
Difference	1.49	0.64	1.65
	(2.39)	(1.06)	(1.31)
All Months	-1.02	0.39	-2.24
	(-1.49)	(0.58)	(-1.62)

Panel C. Year 6-10

Annual	0.34	0.94	0.69
	(0.49)	(1.13)	(0.51)
Nonannual	-1.38	-1.05	-2.29
	(-1.65)	(-1.31)	(-1.89)
Difference	1.72	1.99	2.98
	(2.12)	(2.33)	(2.08)
All Months	-1.48	-0.49	-1.58
	(-1.63)	(-0.63)	(-1.41)

When comparing the performances of the different strategies for the 1-year formation period in the combined German and Swedish sample as shown in Table 5, Panel A, we find that the Annual strategy outperforms the Nonannual strategy for each time subperiod. This outperformance is visible in the performance of the Difference strategy and statistically significant at the 95% level for the whole sample and the second half of the sample. However, the Annual strategy only shows significantly positive returns in the first half of the sample (average monthly return of 126 bps, t-statistic of 2.09). Consequently, the statistical significance of the Difference strategy's returns stems in large part from the significantly negative returns of the Nonannual strategy. Interestingly, the Nonannual and the All Months strategy do not show the positive return characteristics of the one-year momentum effect which is documented for European countries

(Rouwenhorst, 1998 and Griffin, Ji, & Martin, 2003). However, Rouwenhorst (1998) reports that profits from momentum strategies are lowest in the German and Swedish markets. Moreover, the one-month lagged return, which shows significantly negative estimation coefficients in our regression analysis, is included in the formation period for both strategies. This might induce a short-term reversal effect (Jegadeesh, 1990). Also, the most recent financial crisis which is included in our sample can lead to temporal reversion of the momentum effect (Daniel & Moskowitz, 2011). It can be seen in Table 5, Panel A, that the All Months strategy yields positive profits in the first half of the sample, excluding comparable financial crises. Consequently, our findings of negative returns for the Nonannual and the All Months strategy with a 1-year formation period can be consistent with the existing literature based on the results of our regression analysis.

For the 2-5 year formation period (Table 5, Panel B), the Annual strategy does not show any significantly positive returns. Over the whole sample period, the Difference strategy earns statistical significant 149 bps per month on average. Again, this positive return is mainly due to the negative performance of the Nonannual strategy which loses 111 bps per month on average (t-statistic of -1.60). Similarly, the All Months strategy averages -102 bps per month (t-statistic of -1.49) during the whole sample period and -224 bps (t-statistic of -1.62) during the second half. The negative returns of the Nonannual and the All Months strategy for the 2-5 year formation period are consistent with the long-term reversal effect previously documented (De Bondt & Thaler, 1985).

Applying a 6-10 year formation period (Table 5, Panel C), the Annual strategy shows positive returns for all three subperiods. However, those decile spreads are not statistically significant in the combined German and Swedish sample. Similar to the 2-5 year formation period, the Nonannual and the All Months strategy exhibit return reversal effects over the longer 6-10 year horizon. More specifically, the Nonannual strategy earns -138 bps per month when using the whole time period and -229 bps in the second half of the sample. Both returns are statistically significant at the 90% level. In contrast to the 2-5 year horizon, returns on the Difference strategy are statistically significant at the 95% level for all three subperiods, while showing the highest significance in the first half of the sample (t-statistic of 2.33).

In general, the annual strategies perform better in the first half of the combined German and Swedish sample. This is consistent with our previous findings, according to which coefficient estimates at annual lags are higher and more statistical significant in the first half of the sample. In absolute return terms, the Annual strategy based on a 1-year formation period yields the highest return (126 bps in the first half of the sample). Even though there exists research on seasonality strategies on the European market (e.g. Heston & Sadka, 2010), our results for the combined German and Swedish sample are hard to reconcile to this research since our combined sample is very specific. Therefore, we compare and link back our results to the existing literature for the individual German and Swedish samples.

Table 6 **Average Monthly Returns of Trading Strategies based on Past Returns in Germany**

Table 6 reports simple average monthly returns (in percent) of four different long-short trading strategies (Annual, Nonannual, Difference and All Months). The performance is reported for the whole sample (January 1987 to December 2015), for the first half of the sample (January 1987 to December 2000) and for the second half (January 2002 to December 2015). Every month stocks are assigned into decile portfolios of equal size, based on their historical average returns according to various categories. Within a decile portfolio stocks are equally weighted. The return of a strategy is the return on the top decile portfolio minus the return on the bottom decile portfolio. Corresponding t-statistics are reported in parenthesis. Panels A to C report the performances of the strategies for different formation intervals.

Panel A. Year 1

Strategy	Whole sample	First half of the sample	Second half of the sample
Annual	-0.45	1.20	-2.13
	(-0.36)	(2.01)	(-0.86)
Nonannual	-4.62	0.52	-10.17
	(-3.47)	(0.78)	(-3.99)
Difference	4.17	0.68	8.04
	(2.41)	(1.28)	(2.33)
All Months	-4.48	1.10	-10.63
	(-3.31)	(1.67)	(-4.09)

Panel B. Year 2-5

Annual	-0.12	0.55	-0.80
	(-0.16)	(0.99)	(-0.51)
Nonannual	-1.38	-0.02	-2.26
	(-1.72)	(-0.03)	(-1.33)
Difference	1.26	0.57	1.46
	(1.72)	(1.00)	(0.93)
All Months	-1.50	0.11	-2.94
	(-1.92)	(0.16)	(-1.80)

Panel C. Year 6-10

Annual	0.49	1.78	0.47
	(0.63)	(2.06)	(0.29)
Nonannual	-1.75	-1.52	-2.90
	(-1.84)	(-1.92)	(-2.19)
Difference	2.24	3.30	3.37
	(2.31)	(3.83)	(1.89)
All Months	-2.08	-0.81	-2.43
	(-2.06)	(-1.03)	(-2.02)

Table 6, Panel A, reports the performances of the trading strategies for the individual German market. The Annual 1-year strategy yields a negative average monthly return when considering the whole sample and the second half of the sample. These negative decile spreads are not statistically significant. In contrast, the Annual strategy earns significant 120 bps per month (t-statistics of 2.01) on average in the first half of the sample. The Nonannual strategy shows significantly negative average monthly returns for the whole sample period (-462 bps with a t-statistic of -3.47) and the second half of the sample period (-1017 bps with a t-statistic of 3.99). Similarly, the All Months strategy performs badly in the whole sample (-448 bps with a t-statistic of -3.31) and the second half (-1063 bps with a t-statistic of -4.09). However, the All Months strategy earns on average 110 bps per month when considering the first half of the sample separately. This positive average return is significant at the 90% level. The Difference strategy consistently earns positive returns across the three different subperiods. When we compare the results for the 1-year formation period of our whole sample period and the second half of our sample to Heston & Sadka (2010), it shows that our results are quite different. The authors report significantly positive returns for all trading strategies, except for the Difference strategy. This is consistent with the 1-year momentum effect. The momentum effect is absent when looking at the whole period and the second half of our sample, which for the second half is consistent with the results from the regression analysis in chapter 6.2. However, the sample we use (January 1986 to December 2015) extends the Heston & Sadka (2010) horizon (February 1985 to June 2006) by almost ten years and thus includes the 2008 financial crisis and its aftermath. This might lead to distorted results. Daniel & Moskowitz (2011) argue that the momentum effect gets reversed during times of stock market crises and times of high market volatility. Indeed, if we compare our results in the first half of the sample to Heston and Sadka, the results for Germany are more in line: In our sample the Annual strategy earns 120 bps (t-statistic of 2.01) compared to 117 bps (3.23) in Heston & Sadka (2010). Also, our All Months strategy yields 110 bps (1.67) compared to 125 bps (2.91), which is similar in magnitude. The relatively lower t-statistics of our results are likely due to the lower number of observations in the first half our sample.

The Annual strategy based on a 2-5 year formation period (Table 6, Panel B) in the German market does not exhibit any significantly positive returns. That holds for all of the three subperiods. Similarly, Heston & Sadka (2010) cannot find significantly positive returns for Annual strategies based on 2-3 and 4-5 years formation periods in the German market. Our Nonannual and All Months strategies using the 2-5 year formation period feature the long-term reversal effect when considering the whole sample period and the second half separately. The negative average returns are all statistically significant at the 90% level, except for the one of the Nonannual strategy in the second half (t-statistic of 1.33). Heston & Sadka (2010) report similar negative returns for those two strategies in Germany for a 2-3 year formation horizon. Using our whole sample period, the Difference strategy yields an average monthly return of 126 bps, which is significant at the 90% level (t-statistics of 1.72). Heston & Sadka (2010) report 169 bps per month for a 2-3 year formation period and 68 bps for a 4-5 year formation period of the Difference strategy.

Compared to the 2-5 year formation horizon, the Annual strategy based on a 6-10 year horizon (Table 6, Panel C) earns significantly positive returns in the first half of the German sample (178 bps with a t-statistic of 2.06). The return of this strategy is slightly positive in the full sample (49 bps per month) and the second half of the sample (47 bps per month). Corresponding t-statistics, however, suggest that the returns are not significant. Heston and Sadka (2010) do not include a 6-10 year formation horizon in their European study. Therefore, we turn to their U.S. study (2008) to compare results qualitatively. Similar to our results, the Annual strategy based on the longer horizon of 6-10 years performs better than the one with a 2-5 year horizon. For the German sample, this is also consistent with the results from our regression analysis, showing that coefficient estimates at longer annual lags are higher and more significant, in particular for the first half of the sample. The Nonannual and the All Months strategy exhibit negative average monthly returns which are significant at the 90% level for the whole sample and the second half of the sample. Heston & Sadka (2008) also find significantly negative returns for those two strategies. However, the average monthly returns in our sample are more negative and less significant compared to theirs. The 6-10 year Difference strategy in the German market performs best when considering the first half of the sample only (average monthly return of 330 bps, t-statistic of 3.83). This is again consistent with our regression analysis according to which the seasonality pattern is stronger in the first half of the German sample.

Table 7 **Average Monthly Returns of Trading Strategies based on Past Returns in Sweden**

Table 7 reports simple average monthly returns (in percent) of four different long-short trading strategies (Annual, Nonannual, Difference and All Months). The performance is reported for the whole sample (January 1987 to December 2015), for the first half of the sample (January 1987 to December 2000) and for the second half (January 2002 to December 2015). Every month stocks are assigned into decile portfolios of equal size, based on their historical average returns according to various categories. Within a decile portfolio stocks are equally weighted. The return of a strategy is the return on the top decile portfolio minus the return on the bottom decile portfolio. Corresponding t-statistics are reported in parenthesis. Panels A to C report the performances of the strategies for different formation intervals.

Panel A. Year 1

Strategy	Whole sample	First half of the sample	Second half of the sample
Annual	1.89	1.59	2.23
	(2.57)	(1.64)	(2.10)
Nonannual	-0.13	-0.20	-0.15
	(-0.16)	(-0.17)	(-0.12)
Difference	2.02	1.79	2.38
	(2.65)	(1.61)	(2.33)
All Months	0.51	0.90	0.02
	(0.59)	(0.76)	(0.02)

Panel B. Year 2-5

Strategy	Whole sample	First half of the sample	Second half of the sample
Annual	2.10	1.98	1.97
	(2.72)	(1.64)	(1.68)
Nonannual	0.28	2.01	0.29
	(0.35)	(1.36)	(0.24)
Difference	1.82	-0.03	1.68
	(2.52)	(-0.03)	(1.55)
All Months	0.43	2.67	0.30
	(0.49)	(1.76)	(0.23)

Panel C. Year 6-10

Strategy	Whole sample	First half of the sample	Second half of the sample
Annual	1.39 (1.60)	n/a	1.35 (1.20)
Nonannual	0.21 (0.21)	n/a	-0.01 (-0.01)
Difference	1.18 (1.43)	n/a	1.36 (1.44)
All Months	0.07 (0.08)	n/a	-0.03 (-0.02)

Table 7 reports the performance of the trading strategies in the Swedish market. The 1-year Annual strategy (Table 7, Panel A) earns significantly positive monthly average returns of 189 bps (t-statistic of 2.57) in the whole sample period. The positive performance of the strategy is stronger and more statistically significant in the second half of the sample as opposed to the first half. The Nonannual strategy for this formation period shows flat monthly returns on average for all three subperiods, whereas the All Months strategy exhibits slightly positive returns for the whole sample period and the first half. However, those decile spreads are not statistically significant. For the period from February 1985 through June 2006, Heston & Sadka (2010) report positive average returns on all three strategies in the Swedish sample. The Annual strategy yields on average 211 bps per month (t-statistic 4.07) in their study. Taking into account the different sample horizons, the results for the Annual strategy in our analysis are similar. In contrast to that, our results for the Nonannual and All Months strategy differ from their results: in our sample, the two strategies do not show a significantly positive momentum effect. This might be due to the longer time horizon of our sample, including the recent financial crisis. Additionally, the return in lag 1 is included in the formation period of the two strategies. Since the coefficient for the first lag shows significantly negative estimates, this negatively impacts the performance.

Referring again to Daniel & Moskowitz (2011), the absence of a momentum effect in our sample is consistent with their finding that the effect gets reversed during times of stock market crises and times of high market volatility. Moreover, Rouwenhorst (1998) documents that the momentum effect among European markets is weakest in the Swedish market and insignificant, using a sample ranging from 1980 to 1995.

Using a 2-5 year formation period (Table 7, Panel B), the Annual strategy earns 210 bps per month (t-statistic of 2.72), while not displaying a material difference between the first and second half of the sample. Consistent with our finding, Heston & Sadka (2010) report average monthly returns of 117 bps (based on a 2-3 year formation horizon) and of 133 bps (based on a 4-5 year formation horizon) for this Annual strategy in the Swedish market. Following the literature, we would expect a reversal effect for the Nonannual and the All Months strategies using a 2-5 year formation horizon. This is not the case in our sample: both strategies show high positive returns in the first half of the sample. However, only the return of the All Months strategy is statistically significant at the 90% level. Evidence for the existence of a long-term reversal effect in the Swedish market is also mixed in Heston & Sadka (2010). On the one hand, the returns of the Nonannual and the All Months strategy are significantly negative (90% level) for the 2-3 year formation period. On the other hand, the average returns are negative for the 4-5 year formation horizon, but not statistically significant.

In the Swedish sample, the Annual strategy performs best among all trading strategies based on a 6-10 year formation horizon (Table 7, Panel C). Using the whole sample period, the strategy earns 139 bps per month on average. Although this decile spread is not statistically significant (t-statistic of 1.60), compared to the Nonannual (t-statistic 0.21) and the All Months strategy (t-statistic 0.08), its t-statistic is considerably larger. Given the fact that there are relatively fewer observations in the Swedish sample for trading strategies using formation periods with such long horizons, this still speaks to the economic importance and persistence of return seasonalities.

Generally, the annual strategies based on a 1-year and a 2-5 year formation period perform better than the Annual strategies based on a 6-10 year formation period. This is in line with the stronger annual pattern in the first five years in the Swedish sample.

Table 8 **Comparison of Average Monthly Returns of Annual Strategies**

Table 8 reports simple average monthly returns (in percent) of four annual strategies. The performance is reported for the whole sample (January 1987 to December 2015), for the first half of the sample (January 1987 to December 2000) and for the second half (January 2002 to December 2015). Every month stocks are assigned into decile portfolios of equal size, based on their historical average returns across annual lags. Within a decile portfolio stocks are equally weighted. The return of a strategy is the return on the top decile portfolio minus the return on the bottom decile portfolio. Corresponding t-statistics are reported in parenthesis. Panels A to C report the performances of the strategies for different country samples.

Panel A. Germany and Sweden

Annual Strategy	Whole sample	First half of the sample	Second half of the sample
Year 1	0.33	1.26	-0.59
	(0.34)	(2.09)	(-0.32)
Year 2-5	0.38	0.77	-0.12
	(0.59)	(1.33)	(-0.09)
Year 6-10	0.34	0.94	0.69
	(0.49)	(1.13)	(0.51)
Custom	1.19	0.98	1.40
	(1.62)	(1.31)	(0.69)

Panel B. Germany

Year 1	-0.45	1.20	-2.13
	(-0.36)	(2.01)	(-0.86)
Year 2-5	-0.12	0.55	-0.80
	(-0.16)	(0.99)	(-0.51)
Year 6-10	0.49	1.78	0.47
	(0.63)	(2.06)	(0.29)
Custom	1.22	1.41	1.08
	(1.65)	(1.93)	(0.57)

Panel C. Sweden

Annual Strategy	Whole sample	First half of the sample	Second half of the sample
Year 1	1.89	1.59	2.23
	(2.57)	(1.64)	(2.10)
Year 2-5	2.10	1.98	1.97
	(2.72)	(1.64)	(1.68)
Year 6-10	1.39	n/a	1.35
	(1.60)		(1.20)
Custom	2.72	n/a	3.00
	(2.98)		(2.37)

Table 8 compares the performances of the different annual strategies in the three different country samples. We add one additional annual strategy to this comparison, which we call a "custom" strategy. This strategy takes into account the country-specific results from the regression analysis using the whole sample period. Specifically, this strategy uses historical returns at annual lags where estimation coefficients are significantly positive in the formation period.[13]

Table 8, Panel A, shows that the performance of the custom annual strategy is now positive in every three subperiods for the combined German and Swedish sample. The custom strategy shows the best performance in the whole sample and the second half. Corresponding t-statistics also increase compared to the other annual strategies.

Table 8, Panel B, shows that the return of the custom strategy is again positive for all subperiods in Germany. In the whole sample, the custom annual strategy earns 122 bps per month on average. This decile spread is statistically significant at the 90% level. Compared to the negative and slightly positive returns of the three other annual strategies, this is a large improvement. In the first half of the sample, all four strategies show positive average returns. The custom strategy performs better than the Year 1 strategy (141 bps compared to 120 bps) and worse than the Year 6-10 strategy (178 bps). However, the return of the custom strategy is only significant at 90% level, whereas the other two returns are significant at the 95% level. The custom strategy also performs better than the other strategies in the second half of the sample, however its positive average return is not significant.

Table 8, Panel C, shows that the custom annual strategy performs better than all other strategies in all subperiods of the Swedish sample. It also shows the highest performance among all annual strategies across all three samples, confirming that the annual pattern is strongest in Sweden. The decile spread of the custom strategy is also the most significant among the strategies. Similar to the Year 6-10 strategy, the custom strategy cannot be constructed in the first half of the Swedish sample, due to lack of sufficient historical data.

[13] The custom annual strategy for the combined German and Swedish sample uses historical returns in annual lags 12, 24, 36, 48, 72, 84 and 108. The strategy for the German sample uses annual lags 12, 84 and 108 whereas the one for the Swedish market uses annual lags 12, 24, 36, 48, 60, 72, 108 and 120.

7.2 Risk-Adjusted Returns and Practical Considerations of Seasonality Strategies

To determine whether the positive returns of the annual strategies are solely compensation for risk, we examine the covariance between the strategy returns and systematic risk factors. We use the three Fama & French (1993) common risk factors (the market factor, the size factor and the book-to-market equity factor) in this analysis[14]. We use the European version of the three risk factors, where the data is only available from July 1990 onwards. We regress decile spreads (e.g. the annual strategy returns) on zero cost portfolios and therefore can interpret the intercepts of the regressions as risk-adjusted returns. The results of these regressions are reported in Table 9 to Table 11. The results are very similar to our previous analyses in Table 8: risk-adjusted returns of the annual strategies are highest and most significant in the Swedish sample, where six out of eight intercepts are significant at the 99% level and one at the 95% level. For the combined German and Swedish sample and the separate German sample, risk-adjusted returns are significantly positive only in the first half of the sample period.

It is noteworthy that none of the annual strategies show significantly positive exposure to one of the risk factors in the three country samples. When there is significant exposure to a risk factor, the loading is negative. The 2-5 year annual strategy is an exception of this generalization: it exhibits positive exposure to the market factor in the combined German and Swedish sample for the whole period and the first half subperiod. Although, it is not entirely accurate to compare the unadjusted returns (Table 8) with the risk-adjusted ones because of the different time horizons, the comparison shows that there is not a meaningful difference between the returns. This follows from the fact that the seasonality strategies exhibit basically zero exposure to the Fama & French (1993) risk factors.

[14] Returns on these factors are obtained from Kenneth French's website, 2016

Table 9 **Time Series Regression of Decile Spreads on Common Risk Factors for Germany and Sweden**

Table 9 reports estimation coefficients for time series OLS regressions of three different annual decile spreads on the market, size and value factors. The Intercept represents the risk-adjusted return of the annual strategy. We obtain the return data for the risk factors from Kenneth French's webpage. All returns are in USD, include dividends and capital gains, and are not continuously compounded. The European factor returns are only available from July 1990 onwards, so Panel A uses the time period July 1990 through December 2015, Panel B July 1990 through December 2000, and Panel C January 2001 through December 2015. Corresponding t-statistics using robust standard errors are reported in parenthesis (*** p<0.01, ** p<0.05, * p<0.1).

	Panel A. Whole sample			Panel B. First half of the sample			Panel C. Second half of the sample		
	Annual strategy			Annual strategy			Annual strategy		
	Year 1	Year 2-5	Year 6-10	Year 1	Year 2-5	Year 6-10	Year 1	Year 2-5	Year 6-10
Intercept	0.00129	0.00381	0.00355	0.0128***	0.00675*	0.00938	-0.00660	-0.00243	0.00582
	(0.116)	(1.067)	(0.715)	(3.280)	(1.701)	(1.410)	(-0.371)	(-0.333)	(0.403)
Market	-0.0240	0.122*	0.0449	0.0580	0.307**	0.0176	-0.247	0.166	0.111
	(-0.103)	(1.757)	(0.445)	(0.465)	(2.467)	(0.0686)	(-0.808)	(1.263)	(0.323)
Size	-0.0401	-0.0134	-0.0236	-0.211	0.159	-0.00696	-0.164	-0.0136	0.395
	(-0.0833)	(-0.0886)	(-0.0994)	(-1.079)	(0.982)	(-0.0220)	(-0.151)	(-0.0352)	(0.736)
Value	0.309	-0.197	-0.101	-0.348	-0.102	-0.0249	1.137	-0.251	0.00307
	(0.814)	(-1.403)	(-0.769)	(-1.512)	(-0.475)	(-0.120)	(1.506)	(-0.667)	(0.00552)
Observations	305	300	240	125	120	60	168	120	60
R-squared	0.002	0.013	0.002	0.050	0.065	0.001	0.010	0.011	0.009

Table 10 **Time Series Regression of Decile Spreads on Common Risk Factors for Germany**

Table 10 reports estimation coefficients for time series OLS regressions of three different annual decile spreads on the market, size and value factors. The Intercept represents the risk-adjusted return of the annual strategy. We obtain the return data for the risk factors from Kenneth French's webpage. All returns are in USD, include dividends and capital gains, and are not continuously compounded. The European factor returns are only available from July 1990 onwards, so Panel A uses the time period July 1990 through December 2015, Panel B July 1990 through December 2000, and Panel C January 2001 through December 2015. Corresponding t-statistics using robust standard errors are reported in parenthesis (*** p<0.01, ** p<0.05, * p<0.1).

	Panel A. Whole sample			Panel B. First half of the sample			Panel C. Second half of the sample		
	Annual strategy			Annual strategy			Annual strategy		
	Year 1	Year 2-5	Year 6-10	Year 1	Year 2-5	Year 6-10	Year 1	Year 2-5	Year 6-10
Intercept	-0.00963	-0.000786	0.00547	0.00978***	0.00624*	0.0175***	-0.0231	-0.00973	0.00420
	(-0.626)	(-0.190)	(0.922)	(2.748)	(1.792)	(2.833)	(-0.927)	(-1.055)	(0.227)
Market	0.0420	0.0488	-0.0540	0.117	0.0310	0.0178	-0.206	0.209	0.0838
	(0.134)	(0.662)	(-0.539)	(1.053)	(0.347)	(0.0896)	(-0.500)	(1.306)	(0.194)
Size	-0.0840	0.0613	-0.0682	-0.156	0.218	-0.0159	-0.274	-0.137	0.462
	(-0.127)	(0.338)	(-0.251)	(-0.847)	(1.553)	(-0.0537)	(-0.183)	(-0.276)	(0.685)
Value	0.605	-0.184	-0.0669	-0.194	-0.0758	0.0275	1.627	-0.502	0.139
	(1.181)	(-1.092)	(-0.487)	(-0.936)	(-0.330)	(0.155)	(1.569)	(-1.092)	(0.202)
Observations	305	300	240	125	120	60	168	120	60
R-squared	0.004	0.005	0.002	0.042	0.025	0.001	0.011	0.014	0.008

Table 11 **Time Series Regression of Decile Spreads on Common Risk Factors for Sweden**

Table 11 reports estimation coefficients for time series OLS regressions of three different annual decile spreads on the market, size and value factors. The Intercept represents the risk-adjusted return of the annual strategy. We obtain the return data for the risk factors from Kenneth French's webpage. All returns are in USD, include dividends and capital gains, and are not continuously compounded. The European factor returns are only available from July 1990 onwards, so Panel A uses the time period July 1990 through December 2015, Panel B July 1990 through December 2000, and Panel C January 2001 through December 2015. Corresponding t-statistics using robust standard errors are reported in parenthesis (*** p<0.01, ** p<0.05, * p<0.1).

	Panel A. Whole sample			Panel B. First half of the sample			Panel C. Second half of the sample		
	Annual strategy			Annual strategy			Annual strategy		
	Year 1	Year 2-5	Year 6-10	Year 1	Year 2-5	Year 6-10	Year 1	Year 2-5	Year 6-10
Intercept	0.0209***	0.0213***	0.0143***	0.0160**	0.0207***	n/a	0.0235***	0.0213***	0.0113
	(4.812)	(4.247)	(2.818)	(2.278)	(3.397)		(4.862)	(2.891)	(1.550)
Market	-0.0148	-0.0448	0.0753	0.317	-0.130	n/a	-0.299***	-0.112	0.149
	(-0.143)	(-0.480)	(0.679)	(1.360)	(-0.550)		(-3.058)	(-0.929)	(1.139)
Size	0.166	-0.146	-0.152	-0.249	-0.163	n/a	0.298	0.0189	0.303
	(0.688)	(-0.774)	(-0.577)	(-0.728)	(-0.538)		(1.092)	(0.0555)	(0.834)
Value	-0.432**	0.00570	-0.302	-0.783*	-0.191	n/a	0.0402	0.683	-0.279
	(-2.065)	(0.0294)	(-1.053)	(-1.925)	(-0.813)		(0.203)	(1.527)	(-0.766)
Observations	305	238	170	125	58	0	168	120	60
R-squared	0.024	0.002	0.012	0.094	0.018		0.073	0.025	0.022

Lastly, we want to point out that we did not consider transactions costs in our analysis. Our overall analysis of the performance of the seasonality strategies suggests that it is profitable to trade based on average returns across annual lags. Even simply considering the return in the same month one year ago results in significantly positive returns in most of the samples and time periods we examined[15]. Also, higher horizon annual strategies are profitable. However, since the described strategies require monthly rebalancing, portfolio turnover is likely to be as high as 100% per month. This is the case because top and bottom decile portfolio in one month will not be the same in the next, as the ranking of stocks is only based on past returns in one specific calendar month. The transaction costs associated with these annual strategies are most likely to offset the gross profits generated by the strategies. Even though annual seasonality strategies might not be profitable in a real-world application, our analyses show that positive returns of such strategies are most likely not covered by standard risk factors.

[15] Five out of the nine returns are significantly positive, while the remaining are statistically insignificant.

8 Conclusion

Recent studies in the finance literature document a robust and persistent annual seasonality pattern in the cross-section of individual U.S. security returns. Motivated by those results, in a first step, we examine if such an annual pattern also exists in the monthly returns of individual German and Swedish listed common stocks. Additionally, we assess if these stocks show other common return patters, such as the short-term and the momentum effect. In a second step, we investigate if the patterns vary across countries or firm characteristics, and if they are persistent over time or limited to January. In a final step, we test if trading based on an annual seasonality pattern is profitable. By using Fama & MacBeth (1973) cross-sectional regressions we follow a well-grounded approach, one that is used in most recent research in the field of annual return seasonalities. We use a sample of monthly return data for German and Swedish listed common stocks during the period from January 1986 through December 2015.

In the course of our analysis we find that German and Swedish stocks show a seasonal pattern at the annual frequency. This pattern is visible for up to the past ten years. However, it varies across the two countries. In general, we observe a stronger seasonality pattern in Sweden than in Germany. The pattern is more pronounced from years one to five in the Swedish sample, whereas it is stronger at higher annual lags, i.e. years six to ten in Germany. The seasonality effect also varies across firm characteristics, e.g. the effect is clearly visible for big firms whereas it mostly diminishes for firms within the same industries. Moreover, we document that the seasonality pattern is not constant over time: When we split our samples into two time subperiods, we see that in Germany the pattern is stronger in the first than in the second half. In Sweden, however, the pattern is stronger in the second half. Although seasonality is not limited to January, January observations contribute considerably to the overall pattern in Germany. This difference between January and other months cannot be observed in Sweden. In addition to the annual seasonality pattern, we observe a short-term reversal, a momentum and signs of a long-term reversal effect in Germany and in Sweden, mostly independent from firm characteristics and sample period.

Comparing to existing literature, we find that the annual seasonality pattern in Germany and in Sweden is not as pronounced as it is in the U.S. (Heston & Sadka, 2008; Keloharju et al., 2016). The magnitude and statistical significance of estimation coefficients at annual lags are lower in our sample. Heston & Sadka (2010) document seasonality patterns for Europe, Canada, and Japan. In their study, the seasonality pattern among the three geographies is also weakest in Europe. We extend their sample horizon by almost ten years and also report estimation coefficients for lagged returns up to 120 months. In contrast, Heston & Sadka (2010) only estimate coefficients for lagged returns up to 60 months. Moreover, we find that the momentum effect diminishes in the second half of our sample. Since this subperiod includes various financial crises, this finding is consistent with Daniel & Moskowitz (2011), who report that the momentum effect disappears in times of high market volatility.

Testing trading strategies based on historical returns, we discover that annual strategies outperform nonannual strategies significantly. Additionally, these strategies perform better in samples where coefficient estimates at annual lags are higher and more significant. Consequently, those strategies show the highest returns in Sweden. When regressing the returns of the annual strategies on the three Fama & French (1993) risk factors, we find no significant factor loadings. Thus, common risk factors are not able to explain the returns of annual strategies.

When we compare the performance of the annual trading strategies to previous research, we find very similar results as Heston & Sadka (2010) for German and Swedish stocks for the first half of our samples. However, when considering the whole sample and the second half, the performances are more dispersed. We infer from our results, that the recent financial crisis is likely to have had an impact on return seasonalities, since it is included in our sample, but not in Heston & Sadka (2010).

Lastly, we point out some limitations of this paper and relate them to directions for future research. First, compared to U.S. studies on the topic, our data for Germany and Sweden is limited regarding the sample size and time horizon. Related to that, some of the subsamples we construct contain very little observations and thus limit statistical significance. Second, since we conduct only univariate regressions of current month returns on lagged returns, the seasonality pattern might disappear if more explanatory variables are added to the regressions. Consequently, it would be interesting to see which potential explanatory variables absorb the seasonality effect. Some variables like a stock's specific calendar month expected return (Keloharju et al., 2016) or liquidity measures (Heston & Sadka, 2010) are suggested by literature. Third, there are some important considerations with respect to the annual trading strategies: given the fact that the strategies earn significantly positive risk-adjusted returns, it seems likely that there exists an undiscovered systematic risk factor associated with them. However, since we only use three risk factors in our performance analysis, future research could start by extending our approach through adding different risk factors. Moreover, we only report the performance of annual trading strategies before taking into account transaction costs. It would be interesting to see how expensive the implementation of such strategies would be, and if transaction costs could be reduced in some way. Additionally, we construct trading strategies for different formation periods and time periods only. Further research could create strategies for subsets as well, e.g. testing the performance of big firms separately. This would not only be interesting from a performance perspective, but also because trading costs for specific firms might be different. Fourth, our study is limited to German and Swedish common stocks. Thus, it could naturally be extended to other countries and other asset classes, subject to sufficient data availability.

Based on the empirical findings in this paper, we conclude that annual return seasonalities exist in the German and the Swedish stock market and that they vary across the two countries. Robustness checks and annual trading strategies prove the significance and economic importance of such seasonalities. Additionally, the performance of these strategies suggests that the seasonality pattern is of interest not only for academics but also for practitioners.

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Appendix

Appendix A: Tables

Appendix B: Figures

Appendix A
Tables

All tables show the results from monthly univariate Fama MacBeth (1973) regressions of the form $r_{i,t} = a_{k,t} + b_{k,t} r_{i,t-k} + e_{i,t}$, which are calculated for each month *t* and lag *k*, and where $r_{i,t}$ is the return of stock *i* in month *t*. The lagged variable $r_{i,t-k}$ is the return of stock *i* in month *t* - *k*. The regression is calculated for every month *t* from February 1986 through December 2015 (359 months), and for lag *k* values 1 – 120.

For Tables I to XVIII, and XX to XXI, coefficient estimates are reported for lags 1 to 12 and every 12th lag afterwards and separately for different samples: Germany and Sweden combined, Germany only, and Sweden only. The time-series averages of the coefficient estimates as well as t-statistics are reported. The reported Fama MacBeth (1973) t-statistics are corrected for heteroscedasticity and autocorrelation using Newey West (1987) correction with 12 lags (*** p<0.01, ** p<0.05, * p<0.1). Additionally, for each reported lag, the tables show the firm-month observations, the number of months and the average number of firms per month included in the regressions.

Appendix A includes the results for all subsets, i.e. (1) all firms, (2) value, growth, and other firms, (3) big and small firms, (4) high, middle, and low profitability firms, (5) the eight industries, (6) last-month winners and losers, (7) the samples without January observations, and (8) the first and the second half of the time period.

Additionally, Table XIX shows a summary of the results when excluding the observations from each month to compare the difference between excluding January observations to excluding other months.

Table I: All firms

	Germany and Sweden					Germany					Sweden				
Lag	Estimate	t-Stat.	Obser-vations	Months	Avg. no. of firms	Estimate	t-Stat.	Obser-vations	Months	Avg. no. of firms	Estimate	t-Stat.	Obser-vations	Months	Avg. no. of firms
1	-0.0572***	(-5.591)	290,739	359	809.9	-0.0571***	(-4.797)	214,448	359	597.3	-0.0552***	(-4.448)	76,291	359	212.5
2	0.00561	(0.887)	288,091	358	804.7	0.00472	(0.788)	212,570	358	593.8	0.0316**	(2.457)	75,521	358	211.0
3	0.0144**	(2.010)	285,820	357	800.6	0.0106	(1.538)	211,016	357	591.1	0.0244***	(2.702)	74,804	357	209.5
4	0.00657	(0.983)	283,584	356	796.6	0.00751	(1.177)	209,490	356	588.5	0.00824	(0.723)	74,094	356	208.1
5	0.00393	(0.537)	281,374	355	792.6	0.00674	(0.954)	207,985	355	585.9	0.0190*	(1.826)	73,389	355	206.7
6	0.0207***	(3.092)	279,193	354	788.7	0.0188***	(2.679)	206,505	354	583.3	0.0327***	(3.303)	72,688	354	205.3
7	0.00330	(0.683)	277,026	353	784.8	0.00108	(0.235)	205,035	353	580.8	0.0192**	(2.246)	71,991	353	203.9
8	0.00481	(0.899)	274,852	352	780.8	0.00728	(1.362)	203,556	352	578.3	0.00640	(0.919)	71,296	352	202.5
9	0.0167**	(2.536)	272,687	351	776.9	0.0117	(1.462)	202,078	351	575.7	0.0173**	(1.992)	70,609	351	201.2
10	0.0118	(1.599)	270,536	350	773.0	0.0151**	(2.388)	200,609	350	573.2	0.00441	(0.416)	69,927	350	199.8
11	0.0158**	(2.566)	268,401	349	769.1	0.0146**	(2.348)	199,159	349	570.7	0.0142	(1.377)	69,242	349	198.4
12	0.0281***	(4.577)	266,255	348	765.1	0.0254***	(3.827)	197,705	348	568.1	0.0379***	(4.392)	68,550	348	197.0
24	0.0176***	(3.773)	240,514	336	715.8	0.00985**	(1.987)	180,237	336	536.4	0.0474***	(5.825)	60,277	336	179.4
36	0.00891*	(1.749)	215,839	324	666.2	0.00162	(0.291)	163,376	324	504.2	0.0307**	(2.519)	52,463	324	161.9
48	0.00997**	(2.046)	192,698	312	617.6	0.00913	(1.423)	147,285	312	472.1	0.0251*	(1.669)	45,413	312	145.6
60	0.00601	(0.851)	170,960	300	569.9	0.00390	(0.450)	131,972	300	439.9	0.0266***	(3.024)	38,988	300	130.0
72	0.0170***	(2.818)	151,049	288	524.5	0.0120*	(1.846)	117,626	288	408.4	0.0186*	(1.790)	33,423	288	116.1
84	0.0151***	(3.136)	132,571	276	480.3	0.0111**	(2.023)	104,074	276	377.1	0.0120	(1.187)	28,497	276	103.3
96	0.00791	(1.176)	115,474	264	437.4	0.00826	(1.095)	91,264	264	345.7	0.00355	(0.361)	24,210	264	91.7
108	0.0156***	(2.822)	100,181	252	397.5	0.0157**	(2.497)	79,626	252	316.0	0.0224*	(1.936)	20,555	252	81.6
120	-0.00118	(-0.182)	86,898	240	362.1	-0.00437	(-0.624)	69,306	240	288.8	0.0172*	(1.866)	17,592	240	73.3

Table II: Top 30% book-to-market (value firms)

	Germany and Sweden					Germany					Sweden				
Lag	Estimate	t-Stat.	Obser-vations	Months	Avg. no. of firms	Estimate	t-Stat.	Obser-vations	Months	Avg. no. of firms	Estimate	t-Stat.	Obser-vations	Months	Avg. no. of firms
1	-0.0776**	(-2.134)	62,937	336	187.3	-0.0319	(-1.478)	44,388	324	137.0	-0.0891***	(-3.791)	18,437	312	59.1
2	-0.0831	(-1.285)	62,864	336	187.1	-0.0287**	(-2.226)	44,340	324	136.9	0.0236	(1.272)	18,416	312	59.0
3	-0.121	(-0.921)	62,779	336	186.8	-0.0292	(-0.803)	44,302	324	136.7	0.0162	(0.909)	18,387	312	58.9
4	0.116	(1.118)	62,659	336	186.5	0.0630	(1.346)	44,237	324	136.5	-0.0206	(-0.899)	18,347	312	58.8
5	0.149	(1.202)	62,515	336	186.1	0.00704	(0.336)	44,156	324	136.3	0.0257	(1.397)	18,299	312	58.7
6	-0.0211	(-0.564)	62,348	336	185.6	-0.0211	(-0.815)	44,062	324	136.0	0.0135	(0.632)	18,246	312	58.5
7	0.0763	(0.958)	62,154	336	185.0	-0.0242	(-0.816)	43,950	324	135.6	0.0317*	(1.848)	18,184	312	58.3
8	-0.0324	(-1.024)	61,926	336	184.3	0.0380	(1.170)	43,820	324	135.2	0.00738	(0.338)	18,101	312	58.0
9	0.0724**	(2.223)	61,676	336	183.6	-0.0329	(-1.048)	43,675	324	134.8	0.0594***	(2.757)	18,005	312	57.7
10	-0.0114	(-0.286)	61,404	336	182.8	0.00587	(0.380)	43,521	324	134.3	-0.0373	(-1.343)	17,897	312	57.4
11	0.117	(1.138)	61,112	336	181.9	-0.0380	(-0.687)	43,350	324	133.8	0.0136	(0.447)	17,788	312	57.0
12	-0.0447	(-0.618)	60,770	336	180.9	0.0987	(1.620)	43,163	324	133.2	0.0732**	(1.970)	17,650	312	56.6
24	-0.105	(-0.814)	56,163	336	167.2	0.00855	(0.611)	40,490	324	125.0	0.128*	(1.783)	15,913	312	51.0
36	0.0135	(1.008)	50,679	324	156.4	-0.00767	(-0.540)	37,001	324	114.2	-0.103	(-1.038)	14,206	300	47.4
48	-0.00680	(-0.778)	45,232	312	145.0	-0.00192	(-0.233)	33,427	312	107.1	-0.0228	(-0.379)	12,490	297	42.1
60	0.00801	(1.017)	39,893	300	133.0	-6.71e-05	(-0.00788)	29,606	300	98.7	-0.148	(-1.050)	11,042	276	40.0
72	0.00490	(0.462)	35,151	288	122.1	0.00276	(0.256)	26,100	288	90.6	0.0410**	(2.091)	9,676	264	36.7
84	0.0213**	(2.570)	30,714	276	111.3	0.0183**	(2.374)	22,734	276	82.4	-0.000319	(-0.0176)	8,471	264	32.1
96	0.0221**	(2.005)	26,627	264	100.9	0.0151	(1.182)	19,568	264	74.1	0.00569	(0.275)	7,298	264	27.6
108	0.00673	(0.538)	22,790	252	90.4	0.00653	(0.420)	16,667	252	66.1	0.0401	(0.955)	6,192	252	24.6
120	-0.00568	(-0.366)	19,583	240	81.6	-0.00187	(-0.118)	14,293	240	59.6	0.0164	(0.383)	5,246	240	21.9

Table III: Bottom 30% book-to-market (growth firms)

	Germany and Sweden					Germany					Sweden				
Lag	Estimate	t-Stat.	Obser-vations	Months	Avg. no. of firms	Estimate	t-Stat.	Obser-vations	Months	Avg. no. of firms	Estimate	t-Stat.	Obser-vations	Months	Avg. no. of firms
1	0.0770	(0.940)	62,905	336	187.2	-0.0555*	(-1.806)	44,323	324	136.8	0.00710	(0.465)	18,405	312	59.0
2	0.0867	(1.061)	62,743	336	186.7	-0.0811	(-0.892)	44,189	324	136.4	0.0273	(1.431)	18,381	312	58.9
3	-0.0560	(-0.711)	62,551	336	186.2	0.00993	(0.552)	44,038	324	135.9	0.0426***	(3.361)	18,335	312	58.8
4	0.0263	(1.105)	62,328	336	185.5	0.0149	(0.739)	43,859	324	135.4	0.0625**	(2.419)	18,285	312	58.6
5	-0.142	(-1.042)	62,063	336	184.7	-0.00555	(-0.357)	43,668	324	134.8	0.0262	(1.490)	18,207	312	58.4
6	-0.126	(-0.861)	61,759	336	183.8	0.0305*	(1.712)	43,453	324	134.1	0.0517**	(2.529)	18,120	312	58.1
7	0.222	(0.928)	61,408	336	182.8	-0.0151	(-0.457)	43,207	324	133.4	0.0166	(0.903)	18,013	312	57.7
8	-0.0562	(-0.804)	61,000	336	181.5	-0.00171	(-0.0895)	42,928	324	132.5	0.00914	(0.451)	17,880	312	57.3
9	0.0142	(0.695)	60,555	336	180.2	0.0392	(1.131)	42,626	324	131.6	0.0206	(0.776)	17,732	312	56.8
10	0.0266	(1.274)	60,033	336	178.7	-0.0815	(-0.725)	42,275	324	130.5	0.0168	(0.835)	17,558	312	56.3
11	-0.000706	(-0.0438)	59,472	336	177.0	0.0865	(1.089)	41,896	324	129.3	0.00736	(0.684)	17,375	312	55.7
12	0.0533**	(2.446)	58,846	336	175.1	0.0526*	(1.700)	41,490	324	128.1	0.0141	(0.818)	17,148	312	55.0
24	0.0378**	(1.986)	52,234	336	155.5	0.00624	(0.363)	37,463	324	115.6	0.0652***	(3.101)	14,523	312	46.5
36	0.0238*	(1.728)	46,784	324	144.4	0.0527	(1.346)	34,302	324	105.9	-0.0256	(-0.697)	12,277	312	39.3
48	0.00601	(0.588)	41,814	312	134.0	0.00444	(0.355)	31,325	312	100.4	0.0726*	(1.746)	10,421	312	33.4
60	0.00887	(0.893)	36,770	300	122.6	0.0117	(1.033)	28,131	300	93.8	0.0337	(1.521)	8,650	300	28.8
72	0.0144	(1.643)	32,200	288	111.8	0.0131	(1.362)	25,058	288	87.0	-0.0322	(-0.759)	7,114	288	24.7
84	0.0219	(1.430)	27,904	276	101.1	0.00543	(0.321)	22,210	276	80.5	0.0203	(0.733)	5,737	276	20.8
96	0.00481	(0.399)	24,164	264	91.5	0.0238*	(1.662)	19,520	264	73.9	-0.0347	(-1.136)	4,706	264	17.8
108	0.0161	(1.546)	20,814	252	82.6	0.0144	(1.349)	17,052	252	67.7	-0.00749	(-0.228)	3,866	252	15.3
120	0.00362	(0.236)	17,813	240	74.2	0.0115	(0.807)	14,800	240	61.7	0.0147	(0.313)	3,249	240	13.5

Table IV: Middle 40% book-to-market

	Germany and Sweden					Germany					Sweden				
Lag	Estimate	t-Stat.	Obser-vations	Months	Avg. no. of firms	Estimate	t-Stat.	Obser-vations	Months	Avg. no. of firms	Estimate	t-Stat.	Obser-vations	Months	Avg. no. of firms
1	-0.0391**	(-2.537)	84,428	336	251.3	-0.0391***	(-2.701)	59,665	336	177.6	-0.0736***	(-2.692)	25,052	312	80.3
2	0.0220	(1.160)	84,294	336	250.9	0.0255*	(1.670)	59,556	336	177.3	0.0316*	(1.936)	25,019	312	80.2
3	0.0356***	(3.477)	84,149	336	250.4	0.0342***	(3.568)	59,447	336	176.9	0.0296**	(2.533)	24,970	312	80.0
4	0.00150	(0.105)	83,970	336	249.9	0.00682	(0.649)	59,316	336	176.5	-0.0251	(-1.103)	24,913	312	79.8
5	-0.00216	(-0.159)	83,763	336	249.3	0.0124	(0.888)	59,174	336	176.1	0.0103	(0.530)	24,837	312	79.6
6	0.0583**	(2.351)	83,515	336	248.6	0.0331***	(2.899)	58,992	336	175.6	0.0449***	(2.884)	24,749	312	79.3
7	-0.0129	(-0.920)	83,215	336	247.7	0.00568	(0.452)	58,777	336	174.9	0.0237	(1.307)	24,646	312	79.0
8	0.00726	(0.733)	82,865	336	246.6	0.00504	(0.543)	58,530	336	174.2	-0.00637	(-0.535)	24,532	312	78.6
9	-0.00381	(-0.233)	82,488	336	245.5	0.0107	(0.922)	58,267	336	173.4	0.0289**	(2.094)	24,414	312	78.3
10	0.0264***	(2.746)	82,059	336	244.2	0.0227**	(2.214)	57,966	336	172.5	0.00522	(0.220)	24,279	312	77.8
11	0.0133	(1.411)	81,617	336	242.9	0.00130	(0.126)	57,650	336	171.6	0.0170	(0.876)	24,142	312	77.4
12	0.0655***	(3.432)	81,112	336	241.4	0.0398***	(4.127)	57,315	336	170.6	0.0403***	(2.762)	23,962	312	76.8
24	0.0116	(1.438)	75,035	336	223.3	-0.00497	(-0.602)	53,316	336	158.7	0.0663***	(4.695)	21,727	312	69.6
36	0.0114	(0.928)	68,692	324	212.0	0.00979	(0.874)	49,065	324	151.4	0.0207	(1.007)	19,304	312	61.9
48	0.0235**	(2.588)	62,693	312	200.9	0.0207*	(1.956)	45,015	312	144.3	0.0195	(0.909)	17,061	312	54.7
60	0.0163*	(1.817)	56,575	300	188.6	0.00948	(0.968)	41,009	300	136.7	0.0278	(1.269)	14,800	300	49.3
72	0.0284***	(3.256)	50,727	288	176.1	0.0191**	(2.402)	37,239	288	129.3	0.0180	(1.031)	12,891	288	44.8
84	0.00346	(0.460)	45,013	276	163.1	-0.00494	(-0.527)	33,339	276	120.8	-0.000248	(-0.0112)	11,140	276	40.4
96	0.0121	(1.521)	39,526	264	149.7	0.0133*	(1.898)	29,696	264	112.5	0.153	(1.035)	9,529	264	36.1
108	0.0184**	(2.029)	34,742	252	137.9	0.0225**	(1.996)	26,417	252	104.8	-0.0103	(-0.271)	8,152	252	32.3
120	0.0112	(1.492)	30,610	240	127.5	0.00559	(0.646)	23,360	240	97.3	0.0865**	(2.165)	7,058	240	29.4

Table V: Big firms

	Germany and Sweden					Germany					Sweden				
Lag	Estimate	t-Stat.	Obser-vations	Months	Avg. no. of firms	Estimate	t-Stat.	Obser-vations	Months	Avg. no. of firms	Estimate	t-Stat.	Obser-vations	Months	Avg. no. of firms
1	-0.00170	(-0.196)	145,889	359	406.4	-0.000677	(-0.0734)	107,556	359	299.6	-0.0232*	(-1.876)	38,449	359	107.1
2	0.0217**	(2.520)	145,027	358	405.1	0.0210***	(2.711)	106,863	358	298.5	0.0413***	(3.042)	38,280	358	106.9
3	0.0308***	(4.120)	144,235	357	404.0	0.0296***	(3.696)	106,231	357	297.6	0.0388***	(2.958)	38,120	357	106.8
4	0.0185**	(2.582)	143,435	356	402.9	0.0232***	(2.936)	105,604	356	296.6	0.00269	(0.189)	37,960	356	106.6
5	0.00919	(1.198)	142,643	355	401.8	0.0115*	(1.728)	104,970	355	295.7	0.0289**	(1.989)	37,793	355	106.5
6	0.0208***	(2.632)	141,847	354	400.7	0.0187**	(2.210)	104,344	354	294.8	0.0311***	(2.602)	37,627	354	106.3
7	0.0175***	(2.724)	141,068	353	399.6	0.0148**	(2.427)	103,730	353	293.9	0.0293***	(2.827)	37,461	353	106.1
8	0.0100	(1.378)	140,293	352	398.6	0.0131**	(2.204)	103,133	352	293.0	-0.00817	(-0.704)	37,293	352	105.9
9	0.0213***	(2.874)	139,526	351	397.5	0.0185*	(1.951)	102,545	351	292.2	0.00668	(0.568)	37,119	351	105.8
10	0.0179*	(1.960)	138,764	350	396.5	0.0215***	(2.768)	101,959	350	291.3	0.0106	(0.752)	36,943	350	105.6
11	0.0156*	(1.869)	137,996	349	395.4	0.0192**	(2.497)	101,377	349	290.5	0.00851	(0.549)	36,768	349	105.4
12	0.0317***	(3.976)	137,230	348	394.3	0.0324***	(4.185)	100,799	348	289.7	0.0320**	(2.528)	36,590	348	105.1
24	0.0164***	(2.660)	128,209	336	381.6	0.0108	(1.626)	94,076	336	280.0	0.0403***	(3.869)	34,209	336	101.8
36	0.00737	(1.424)	119,313	324	368.3	0.00226	(0.436)	87,624	324	270.4	0.0239*	(1.897)	31,634	324	97.6
48	0.00558	(0.844)	110,203	312	353.2	0.00601	(0.923)	81,070	312	259.8	0.0269	(1.493)	28,996	312	92.9
60	0.00916	(1.561)	101,133	300	337.1	0.00915	(1.229)	74,618	300	248.7	0.0285***	(3.110)	26,367	300	87.9
72	0.0201***	(3.322)	92,096	288	319.8	0.0181***	(3.429)	68,287	288	237.1	0.0104	(0.747)	23,779	288	82.6
84	0.0112*	(1.946)	83,257	276	301.7	0.0107*	(1.900)	62,083	276	224.9	0.00318	(0.308)	21,203	276	76.8
96	0.0147**	(2.051)	74,659	264	282.8	0.0220***	(2.724)	55,921	264	211.8	0.000388	(0.0345)	18,772	264	71.1
108	0.0132**	(2.200)	66,479	252	263.8	0.0188***	(2.678)	49,973	252	198.3	0.0143	(1.150)	16,589	252	65.8
120	0.0148**	(2.257)	58,964	240	245.7	0.0161**	(2.538)	44,456	240	185.2	0.0186*	(1.862)	14,617	240	60.9

Table VI: Small firms

	Germany and Sweden					Germany					Sweden				
Lag	Estimate	t-Stat.	Obser-vations	Months	Avg. no. of firms	Estimate	t-Stat.	Obser-vations	Months	Avg. no. of firms	Estimate	t-Stat.	Obser-vations	Months	Avg. no. of firms
1	-0.0769***	(-7.140)	144,916	359	403.7	-0.0761***	(-6.023)	107,021	359	298.1	-0.0687***	(-5.058)	37,992	359	105.8
2	-0.000394	(-0.0610)	143,137	358	399.8	-0.00253	(-0.393)	105,840	358	295.6	0.0266*	(1.795)	37,394	358	104.5
3	0.0105	(1.314)	141,664	357	396.8	0.00605	(0.789)	104,920	357	293.9	0.0163	(1.647)	36,838	357	103.2
4	0.00351	(0.462)	140,231	356	393.9	0.00191	(0.287)	104,024	356	292.2	0.00496	(0.320)	36,290	356	101.9
5	0.00309	(0.388)	138,816	355	391.0	0.00588	(0.709)	103,155	355	290.6	0.0108	(1.119)	35,750	355	100.7
6	0.0221***	(2.936)	137,435	354	388.2	0.0202**	(2.516)	102,299	354	289.0	0.0308**	(2.342)	35,215	354	99.5
7	-0.000892	(-0.185)	136,051	353	385.4	-0.00265	(-0.495)	101,445	353	287.4	0.0178	(1.528)	34,683	353	98.3
8	0.00560	(0.966)	134,659	352	382.6	0.00884	(1.129)	100,563	352	285.7	0.0189*	(1.655)	34,155	352	97.0
9	0.0167**	(2.364)	133,267	351	379.7	0.00995	(1.294)	99,674	351	284.0	0.0289***	(2.614)	33,643	351	95.8
10	0.00816	(1.150)	131,884	350	376.8	0.0105*	(1.656)	98,791	350	282.3	0.000759	(0.0571)	33,137	350	94.7
11	0.0149**	(2.505)	130,521	349	374.0	0.00970	(1.539)	97,922	349	280.6	0.0106	(1.154)	32,627	349	93.5
12	0.0264***	(4.691)	129,142	348	371.1	0.0249***	(3.766)	97,045	348	278.9	0.0415***	(3.614)	32,114	348	92.3
24	0.0192***	(2.934)	112,444	336	334.7	0.0104*	(1.746)	86,299	336	256.8	0.333	(1.139)	26,205	334	78.5
36	0.00988	(1.605)	96,653	324	298.3	0.00302	(0.407)	75,866	324	234.2	0.0287	(1.557)	20,943	320	65.4
48	0.0102*	(1.696)	82,599	312	264.7	0.00971	(1.203)	66,313	312	212.5	-0.604	(-0.981)	16,509	303	54.5
60	0.00592	(0.657)	69,916	300	233.1	0.00275	(0.276)	57,440	300	191.5	0.0101	(0.272)	12,692	290	43.8
72	0.0132	(1.442)	59,030	288	205.0	0.00264	(0.264)	49,404	288	171.5	0.180	(1.110)	9,695	276	35.1
84	0.0203**	(1.980)	49,376	276	178.9	0.0101	(0.995)	42,042	276	152.3	1.176*	(1.796)	7,332	262	28.0
96	-0.0165	(-1.211)	40,869	264	154.8	-0.0106	(-0.688)	35,386	264	134.0	-0.121	(-0.638)	5,469	240	22.8
108	0.0191	(1.185)	33,746	252	133.9	0.0278	(1.070)	29,688	252	117.8	0.0218	(0.170)	3,995	217	18.4
120	-0.0386**	(-2.148)	27,970	240	116.5	-0.0448**	(-2.504)	24,877	240	103.7	0.207*	(1.674)	3,003	186	16.1

Table VII: High profitability firms (top 30%)

	Germany and Sweden					Germany					Sweden				
Lag	Estimate	t-Stat.	Obser-vations	Months	Avg. no. of firms	Estimate	t-Stat.	Obser-vations	Months	Avg. no. of firms	Estimate	t-Stat.	Obser-vations	Months	Avg. no. of firms
1	-0.00628	(-0.554)	55,330	312	177.3	-0.00651	(-0.471)	38,665	312	123.9	-0.0462	(-1.267)	16,499	312	52.9
2	0.0423***	(3.919)	54,935	312	176.1	0.0350***	(3.354)	38,369	312	123.0	0.0794***	(3.363)	16,405	312	52.6
3	0.0489***	(4.817)	54,562	312	174.9	0.0477***	(4.732)	38,096	312	122.1	0.0421**	(2.444)	16,311	312	52.3
4	0.0272***	(3.845)	54,195	312	173.7	0.0316***	(3.664)	37,832	312	121.3	0.0314**	(2.372)	16,217	312	52.0
5	0.0343***	(4.004)	53,836	312	172.6	0.0406***	(3.821)	37,577	312	120.4	0.0404**	(2.087)	16,121	312	51.7
6	0.0181	(1.643)	53,478	312	171.4	0.0281**	(1.986)	37,322	312	119.6	0.0165	(1.040)	16,025	312	51.4
7	0.0270***	(3.303)	53,113	312	170.2	0.0199**	(2.174)	37,061	312	118.8	0.0118	(0.562)	15,926	312	51.0
8	0.0224**	(2.363)	52,734	312	169.0	0.0308***	(3.781)	36,785	312	117.9	-0.00325	(-0.145)	15,827	312	50.7
9	0.0246***	(2.985)	52,358	312	167.8	0.0256***	(3.063)	36,514	312	117.0	0.0258	(1.466)	15,728	312	50.4
10	0.00753	(0.821)	51,989	312	166.6	0.00800	(0.719)	36,250	312	116.2	-0.0285	(-1.032)	15,623	312	50.1
11	0.0132	(1.443)	51,621	312	165.5	0.0240***	(2.994)	35,990	312	115.4	0.00657	(0.217)	15,516	312	49.7
12	0.0323***	(2.747)	51,256	312	164.3	0.0319**	(2.464)	35,733	312	114.5	0.0340	(1.572)	15,405	312	49.4
24	0.00963	(1.271)	47,029	312	150.7	-0.00148	(-0.196)	32,802	312	105.1	0.0578**	(2.490)	14,041	312	45.0
36	0.0162**	(2.372)	43,025	312	137.9	0.0103	(1.282)	30,088	312	96.4	0.00121	(0.0459)	12,763	312	40.9
48	0.00239	(0.312)	39,273	312	125.9	0.00602	(0.636)	27,593	312	88.4	0.0930*	(1.850)	11,423	312	36.6
60	0.00281	(0.277)	35,390	300	118.0	0.00469	(0.537)	24,903	300	83.0	-0.0864	(-1.015)	10,234	300	34.1
72	0.00902	(1.108)	31,878	288	110.7	-0.00450	(-0.502)	22,449	288	77.9	-0.0113	(-0.363)	9,127	288	31.7
84	-0.0104	(-0.939)	28,452	276	103.1	-0.0200*	(-1.722)	20,159	276	73.0	0.0539	(1.247)	8,023	276	29.1
96	0.00979	(1.005)	25,181	264	95.4	0.00127	(0.134)	17,882	264	67.7	0.0573	(0.924)	7,007	264	26.5
108	0.00637	(0.750)	22,270	252	88.4	0.00816	(0.717)	15,874	252	63.0	0.0817	(1.278)	6,183	252	24.5
120	0.00827	(0.935)	19,587	240	81.6	0.00907	(0.878)	14,037	240	58.5	0.0537	(1.509)	5,440	240	22.7

Table VIII: Low profitability firms (bottom 30%)

	Germany and Sweden					Germany					Sweden				
Lag	Estimate	t-Stat.	Obser-vations	Months	Avg. no. of firms	Estimate	t-Stat.	Obser-vations	Months	Avg. no. of firms	Estimate	t-Stat.	Obser-vations	Months	Avg. no. of firms
1	-0.0505***	(-5.543)	55,149	312	176.8	-0.0362***	(-3.740)	38,722	312	124.1	-0.0491**	(-1.991)	16,299	312	52.2
2	0.000657	(0.102)	54,655	312	175.2	-0.00470	(-0.660)	38,442	312	123.2	0.0351**	(2.057)	16,091	312	51.6
3	0.0130*	(1.946)	54,193	312	173.7	0.00866	(1.221)	38,196	312	122.4	0.00959	(0.474)	15,884	312	50.9
4	0.00997	(1.370)	53,734	312	172.2	0.00470	(0.555)	37,956	312	121.7	0.00663	(0.379)	15,676	312	50.2
5	0.00520	(0.897)	53,265	312	170.7	0.00878	(1.103)	37,710	312	120.9	0.0305	(1.399)	15,465	312	49.6
6	0.0215***	(2.774)	52,795	312	169.2	0.00561	(0.626)	37,462	312	120.1	0.0503***	(2.767)	15,253	312	48.9
7	-0.00904	(-1.093)	52,326	312	167.7	-0.0144*	(-1.854)	37,210	312	119.3	-0.0301	(-0.894)	15,043	312	48.2
8	-0.00845	(-1.135)	51,844	312	166.2	-0.00846	(-1.109)	36,954	312	118.4	0.0226	(0.990)	14,828	312	47.5
9	0.0102	(1.175)	51,357	312	164.6	-2.80e-05	(-0.00311)	36,696	312	117.6	-0.00715	(-0.334)	14,614	312	46.8
10	-0.00787	(-0.896)	50,858	312	163.0	-0.00528	(-0.683)	36,427	312	116.8	-0.00985	(-0.487)	14,401	312	46.2
11	-0.00279	(-0.434)	50,356	312	161.4	-0.0121	(-1.514)	36,154	312	115.9	0.0153	(0.739)	14,188	312	45.5
12	0.0266***	(3.189)	49,847	312	159.8	0.0237***	(2.597)	35,877	312	115.0	0.0149	(0.668)	13,976	312	44.8
24	0.00608	(0.816)	43,432	312	139.2	-0.00746	(-0.708)	32,234	312	103.3	0.0468*	(1.770)	11,484	312	36.8
36	0.0166**	(2.002)	37,230	312	119.3	0.00161	(0.175)	28,557	312	91.5	0.132	(1.315)	9,213	312	29.5
48	0.00428	(0.410)	31,869	312	102.1	0.00475	(0.355)	25,298	312	81.1	0.00844	(0.131)	7,282	312	23.3
60	0.0140	(1.179)	26,900	300	89.7	0.0107	(0.609)	22,149	300	73.8	-0.00331	(-0.0719)	5,507	291	18.9
72	0.0107	(0.790)	22,588	288	78.4	0.0261	(1.220)	19,346	288	67.2	-0.197	(-0.819)	4,061	246	16.5
84	-0.0219	(-1.137)	18,821	276	68.2	-0.0271	(-1.239)	16,605	276	60.2	-0.0335	(-0.108)	3,020	228	13.2
96	0.0321	(1.401)	15,635	264	59.2	0.0405	(1.457)	14,214	264	53.8	-0.164	(-1.057)	2,227	197	11.3
108	0.00626	(0.314)	12,874	252	51.1	-0.0406	(-1.168)	11,977	252	47.5	-1.389	(-1.528)	1,768	180	9.8
120	-0.0280	(-0.716)	10,628	240	44.3	0.00539	(0.135)	10,138	240	42.2	0.114	(0.585)	1,384	168	8.2

Table IX: Middle profitability firms (middle 40%)

	Germany and Sweden					Germany					Sweden				
Lag	Estimate	t-Stat.	Obser-vations	Months	Avg. no. of firms	Estimate	t-Stat.	Obser-vations	Months	Avg. no. of firms	Estimate	t-Stat.	Obser-vations	Months	Avg. no. of firms
1	-1.114	(-1.043)	74,572	324	230.2	-1.120	(-1.048)	52,394	324	161.7	-0.0531***	(-3.578)	22,472	312	72.0
2	-0.747	(-0.998)	74,165	324	228.9	-0.749	(-1.002)	52,123	324	160.9	0.0331**	(2.148)	22,325	312	71.6
3	-0.678	(-0.953)	73,797	324	227.8	-0.685	(-0.964)	51,884	324	160.1	0.0549***	(3.562)	22,181	312	71.1
4	0.745	(1.045)	73,434	324	226.6	0.749	(1.051)	51,643	324	159.4	0.00169	(0.0986)	22,039	312	70.6
5	-1.571	(-1.007)	73,073	324	225.5	-1.576	(-1.010)	51,401	324	158.6	0.0200	(1.081)	21,900	312	70.2
6	0.418	(1.068)	72,707	324	224.4	0.412	(1.051)	51,156	324	157.9	0.0195	(1.372)	21,762	312	69.8
7	-0.0326	(-0.753)	72,340	324	223.3	-0.0240	(-0.554)	50,914	324	157.1	0.0160	(0.893)	21,625	312	69.3
8	0.106	(1.205)	71,988	324	222.2	0.103	(1.178)	50,679	324	156.4	-0.00161	(-0.0996)	21,493	312	68.9
9	-0.0316	(-0.583)	71,639	324	221.1	-0.0296	(-0.530)	50,442	324	155.7	0.0192	(1.259)	21,360	312	68.5
10	0.0696	(1.327)	71,279	324	220.0	0.0665	(1.262)	50,196	324	154.9	-0.0220	(-1.205)	21,229	312	68.0
11	0.00388	(0.179)	70,913	324	218.9	0.000209	(0.00973)	49,944	324	154.1	0.0144	(0.795)	21,098	312	67.6
12	0.231	(1.218)	70,547	324	217.7	0.226	(1.187)	49,694	324	153.4	0.0261**	(2.003)	20,965	312	67.2
24	0.0987	(1.136)	65,888	324	203.4	0.0863	(0.995)	46,581	324	143.8	0.0268*	(1.713)	19,207	312	61.6
36	0.0643	(1.017)	61,177	324	188.8	0.0569	(0.894)	43,493	324	134.2	0.00329	(0.121)	17,318	312	55.5
48	0.00325	(0.490)	56,257	312	180.3	0.00702	(0.740)	40,230	312	128.9	0.0260	(1.486)	15,573	312	49.9
60	0.0177**	(2.240)	51,116	300	170.4	0.0126	(1.214)	36,831	300	122.8	0.0269	(1.354)	13,782	300	45.9
72	0.0195**	(2.477)	45,917	288	159.4	0.0176*	(1.800)	33,262	288	115.5	0.0228	(1.151)	12,138	288	42.1
84	0.00701	(0.951)	40,859	276	148.0	0.00844	(1.118)	29,814	276	108.0	-0.00322	(-0.167)	10,511	276	38.1
96	0.0217**	(2.147)	35,912	264	136.0	0.0174	(1.603)	26,325	264	99.7	0.0126	(0.708)	9,073	264	34.4
108	0.0138	(1.488)	31,336	252	124.3	0.0108	(1.006)	23,112	252	91.7	-0.0192	(-0.835)	7,566	252	30.0
120	0.00653	(0.651)	27,464	240	114.4	-0.00148	(-0.144)	20,271	240	84.5	0.0427*	(1.895)	6,409	240	26.7

Table X: Last-month winners

	Germany and Sweden					Germany					Sweden				
Lag	Estimate	t-Stat.	Obser-vations	Months	Avg. no. of firms	Estimate	t-Stat.	Obser-vations	Months	Avg. no. of firms	Estimate	t-Stat.	Obser-vations	Months	Avg. no. of firms
1	-0.0477***	(-4.731)	131,511	359	366.3	-0.0389***	(-3.472)	96,301	359	268.2	-0.0710***	(-5.153)	35,389	359	98.6
2	0.0243**	(2.507)	130,338	358	364.1	0.0292***	(2.937)	95,488	358	266.7	0.0521***	(2.979)	35,030	358	97.8
3	0.0291***	(3.541)	129,177	357	361.8	0.0241***	(2.779)	94,616	357	265.0	0.0431***	(3.238)	34,699	357	97.2
4	0.0193**	(2.543)	128,121	356	359.9	0.0128	(1.437)	93,875	356	263.7	0.0398***	(3.101)	34,388	356	96.6
5	0.0229***	(2.702)	127,149	355	358.2	0.0214**	(2.127)	93,185	355	262.5	0.0361***	(3.702)	34,069	355	96.0
6	0.0266***	(3.471)	126,227	354	356.6	0.0198**	(2.251)	92,540	354	261.4	0.0531***	(4.322)	33,753	354	95.3
7	0.00242	(0.386)	125,270	353	354.9	-0.000644	(-0.0994)	91,890	353	260.3	0.0385***	(3.765)	33,458	353	94.8
8	0.0165**	(2.247)	124,297	352	353.1	0.0225***	(3.493)	91,262	352	259.3	0.0249**	(2.302)	33,141	352	94.2
9	0.0207***	(2.785)	123,428	351	351.6	0.0209**	(2.497)	90,688	351	258.4	0.0106	(0.705)	32,826	351	93.5
10	0.0146	(1.473)	122,432	350	349.8	0.0198**	(2.013)	90,018	350	257.2	-0.000996	(-0.0857)	32,493	350	92.8
11	0.0162**	(2.209)	121,481	349	348.1	0.0176**	(2.058)	89,364	349	256.1	0.0120	(1.282)	32,197	349	92.3
12	0.0342***	(4.646)	120,581	348	346.5	0.0332***	(3.973)	88,777	348	255.1	0.0520***	(3.804)	31,894	348	91.6
24	0.0196***	(2.924)	109,421	336	325.7	0.0140*	(1.860)	81,217	336	241.7	0.0447***	(4.473)	28,246	336	84.1
36	0.0113	(1.365)	98,698	324	304.6	0.00692	(0.814)	73,938	324	228.2	0.0393***	(2.921)	24,795	324	76.5
48	0.0155**	(2.580)	88,471	312	283.6	0.0156**	(1.985)	66,962	312	214.6	0.0124	(0.936)	21,572	312	69.1
60	0.00922	(0.940)	78,797	300	262.7	0.0106	(1.057)	60,277	300	200.9	0.0133	(0.836)	18,602	300	62.0
72	0.0140*	(1.655)	69,913	288	242.8	0.0101	(1.168)	53,985	288	187.4	0.0152	(1.185)	16,078	288	55.8
84	0.0257***	(3.327)	61,623	276	223.3	0.0303***	(3.370)	47,876	276	173.5	-0.0183	(-0.848)	13,791	276	50.0
96	0.00689	(0.833)	53,821	264	203.9	0.00422	(0.442)	41,971	264	159.0	-0.0153	(-0.396)	11,862	264	44.9
108	0.0110	(1.055)	46,857	252	185.9	0.0111	(1.011)	36,691	252	145.6	-0.0320	(-1.037)	10,163	252	40.3
120	-0.0172*	(-1.718)	40,656	240	169.4	-0.0215*	(-1.690)	31,993	240	133.3	0.00791	(0.368)	8,695	240	36.2

Table XI: Last-month losers

	Germany and Sweden					Germany					Sweden				
Lag	Estimate	t-Stat.	Obser-vations	Months	Avg. no. of firms	Estimate	t-Stat.	Obser-vations	Months	Avg. no. of firms	Estimate	t-Stat.	Obser-vations	Months	Avg. no. of firms
1	-0.133***	(-5.680)	159,228	359	443.5	-0.147***	(-5.279)	118,147	359	329.1	-0.0668**	(-2.443)	40,902	359	113.9
2	-0.0114	(-1.573)	157,753	358	440.7	-0.0157**	(-2.082)	117,082	358	327.0	0.0233*	(1.764)	40,491	358	113.1
3	0.00131	(0.161)	156,327	357	437.9	0.00148	(0.189)	116,126	357	325.3	0.00549	(0.555)	40,063	357	112.2
4	0.00122	(0.153)	155,119	356	435.7	0.00744	(1.077)	115,318	356	323.9	-0.0179	(-1.086)	39,659	356	111.4
5	-0.00548	(-0.787)	153,860	355	433.4	-0.00197	(-0.327)	114,489	355	322.5	0.00755	(0.540)	39,266	355	110.6
6	0.0147**	(1.979)	152,580	354	431.0	0.0199**	(2.574)	113,637	354	321.0	0.0215*	(1.744)	38,877	354	109.8
7	0.00619	(0.950)	151,369	353	428.8	0.00181	(0.289)	112,813	353	319.6	0.00938	(0.792)	38,478	353	109.0
8	-0.00525	(-0.879)	150,168	352	426.6	-0.00479	(-0.691)	111,959	352	318.1	-0.00236	(-0.203)	38,103	352	108.2
9	0.0123	(1.625)	148,863	351	424.1	0.00149	(0.143)	111,052	351	316.4	0.0299**	(2.358)	37,725	351	107.5
10	0.00815	(0.991)	147,698	350	422.0	0.00805	(1.130)	110,244	350	315.0	0.0114	(0.815)	37,375	350	106.8
11	0.0170**	(2.220)	146,512	349	419.8	0.0108	(1.488)	109,444	349	313.6	0.0142	(1.134)	36,988	349	106.0
12	0.0261***	(3.648)	145,277	348	417.5	0.0247***	(2.787)	108,582	348	312.0	0.0319***	(3.252)	36,605	348	105.2
24	0.0151**	(2.312)	130,729	336	389.1	0.00801	(1.234)	98,690	336	293.7	0.0534***	(3.372)	31,997	336	95.2
36	0.00976	(1.356)	116,829	324	360.6	0.00282	(0.398)	89,158	324	275.2	0.0322**	(2.066)	27,636	324	85.3
48	0.00355	(0.519)	103,963	312	333.2	0.000933	(0.113)	80,084	312	256.7	0.0352*	(1.824)	23,816	312	76.3
60	0.00480	(0.535)	91,941	300	306.5	-0.00306	(-0.253)	71,490	300	238.3	0.0656**	(2.015)	20,369	300	67.9
72	0.0166**	(2.333)	80,953	288	281.1	0.0121*	(1.714)	63,469	288	220.4	0.0225	(1.054)	17,334	288	60.2
84	0.0161**	(2.037)	70,814	276	256.6	0.00144	(0.167)	56,071	276	203.2	0.00644	(0.369)	14,699	276	53.3
96	0.00728	(0.796)	61,546	264	233.1	0.0120	(1.154)	49,192	264	186.3	-0.00151	(-0.103)	12,342	264	46.8
108	0.0151*	(1.872)	53,250	252	211.3	0.0173*	(1.825)	42,864	252	170.1	0.00832	(0.380)	10,389	252	41.2
120	0.00201	(0.181)	46,190	240	192.5	4.24e-05	(0.00368)	37,264	240	155.3	-0.0108	(-0.466)	8,894	240	37.1

Table XII: Industry 1 to 4 for Germany and Sweden

	Industry 1					Industry 2					Industry 3					Industry 4				
Lag	Estimate	t-Stat.	Obser-vations	Months	Avg. no. of firms	Estimate	t-Stat.	Obser-vations	Months	Avg. no. of firms	Estimate	t-Stat.	Obser-vations	Months	Avg. no. of firms	Estimate	t-Stat.	Obser-vations	Months	Avg. no. of firms
1	-0.0347	(-1.601)	11,262	359	31.4	-0.0669***	(-3.678)	18,128	359	50.5	-0.0739***	(-6.928)	64,815	359	180.5	-0.0628***	(-5.120)	59,496	359	165.7
2	-0.0101	(-0.614)	11,162	358	31.2	-0.0144	(-0.905)	17,962	358	50.2	-0.00508	(-0.664)	64,267	358	179.5	0.0137	(1.265)	59,009	358	164.8
3	0.0203	(1.051)	11,070	357	31.0	0.0102	(0.833)	17,830	357	49.9	0.00824	(0.974)	63,810	357	178.7	0.0102	(1.056)	58,582	357	164.1
4	0.0187	(1.099)	10,981	356	30.8	0.0177	(1.030)	17,703	356	49.7	0.00950	(0.983)	63,360	356	178.0	0.00556	(0.513)	58,165	356	163.4
5	-0.00423	(-0.219)	10,891	355	30.7	-0.000877	(-0.0779)	17,581	355	49.5	-0.00122	(-0.153)	62,914	355	177.2	0.00579	(0.574)	57,752	355	162.7
6	0.00888	(0.442)	10,803	354	30.5	0.0233	(1.609)	17,460	354	49.3	0.0175**	(2.220)	62,473	354	176.5	0.0159*	(1.737)	57,342	354	162.0
7	-0.0101	(-0.440)	10,716	353	30.4	-0.00728	(-0.542)	17,335	353	49.1	0.00851	(1.118)	62,040	353	175.8	0.00649	(0.685)	56,932	353	161.3
8	-0.00509	(-0.272)	10,628	352	30.2	0.00213	(0.182)	17,211	352	48.9	-0.00534	(-0.668)	61,607	352	175.0	-0.00536	(-0.578)	56,524	352	160.6
9	0.0325	(1.624)	10,541	351	30.0	0.000798	(0.0560)	17,095	351	48.7	0.0212***	(2.829)	61,166	351	174.3	0.0122	(1.362)	56,127	351	159.9
10	0.0262	(1.356)	10,456	350	29.9	0.0261*	(1.809)	16,982	350	48.5	0.00895	(0.954)	60,730	350	173.5	0.0165**	(2.157)	55,727	350	159.2
11	0.0308*	(1.735)	10,369	349	29.7	0.0169	(1.139)	16,866	349	48.3	0.0108	(1.208)	60,299	349	172.8	0.0197**	(2.306)	55,323	349	158.5
12	0.0304	(1.523)	10,279	348	29.5	0.0251*	(1.774)	16,745	348	48.1	0.0218***	(2.779)	59,865	348	172.0	0.0160*	(1.734)	54,920	348	157.8
24	-0.0134	(-0.618)	9,223	336	27.4	0.00201	(0.150)	15,324	336	45.6	0.00929	(1.061)	54,688	336	162.8	0.0117	(1.257)	50,069	336	149.0
36	-0.0168	(-0.787)	8,197	324	25.3	-0.000367	(-0.0302)	13,935	324	43.0	0.0219***	(2.632)	49,663	324	153.3	-0.00160	(-0.206)	45,409	324	140.2
48	-0.0250	(-1.204)	7,256	312	23.3	0.0165	(1.183)	12,592	312	40.4	0.00770	(0.832)	44,870	312	143.8	0.00552	(0.662)	40,979	312	131.3
60	-0.00636	(-0.287)	6,364	300	21.2	-0.00184	(-0.0962)	11,324	300	37.7	-0.000887	(-0.0894)	40,289	300	134.3	0.00984	(0.982)	36,847	300	122.8
72	-0.00784	(-0.357)	5,526	288	19.2	0.00328	(0.263)	10,145	288	35.2	0.0177	(1.393)	36,036	288	125.1	0.0174*	(1.776)	33,027	288	114.7
84	0.0359**	(1.986)	4,758	276	17.2	0.0430**	(2.171)	9,009	276	32.6	0.00628	(0.668)	32,024	276	116.0	0.0152	(1.213)	29,441	276	106.7
96	0.0133	(0.580)	4,049	264	15.3	0.00360	(0.136)	7,995	264	30.3	0.0133	(0.990)	28,328	264	107.3	-0.000260	(-0.0241)	26,049	264	98.7
108	0.00246	(0.0959)	3,463	252	13.7	0.00973	(0.385)	7,103	252	28.2	0.0240*	(1.878)	25,017	252	99.3	0.0305**	(2.170)	22,871	252	90.8
120	0.0407	(1.181)	3,004	240	12.5	-0.0441	(-1.366)	6,394	240	26.6	0.000867	(0.0735)	22,076	240	92.0	0.000559	(0.0543)	20,027	240	83.4

Table XIII: Industry 5 to 8 for Germany and Sweden

	Industry 5					Industry 6					Industry 7					Industry 8				
Lag	Estimate	t-Stat.	Obser-vations	Months	Avg. no. of firms	Estimate	t-Stat.	Obser-vations	Months	Avg. no. of firms	Estimate	t-Stat.	Obser-vations	Months	Avg. no. of firms	Estimate	t-Stat.	Obser-vations	Months	Avg. no. of firms
1	-0.0446**	(-2.366)	20,886	359	58.2	-0.0606***	(-3.819)	44,521	359	124.0	-0.0634*	(-1.748)	53,559	359	149.2	-0.0588**	(-1.967)	12,916	359	36.0
2	-0.00476	(-0.248)	20,711	358	57.9	0.00138	(0.117)	44,059	358	123.1	0.134*	(1.965)	53,114	358	148.4	0.0198	(0.601)	12,784	358	35.7
3	-0.0146	(-0.836)	20,539	357	57.5	0.0147	(1.195)	43,688	357	122.4	0.0649	(1.626)	52,684	357	147.6	-0.00790	(-0.262)	12,681	357	35.5
4	0.0321*	(1.737)	20,367	356	57.2	-0.0156	(-1.043)	43,326	356	121.7	0.0467**	(2.234)	52,252	356	146.8	-0.00986	(-0.334)	12,578	356	35.3
5	0.00405	(0.156)	20,195	355	56.9	-0.00652	(-0.456)	42,971	355	121.0	0.0440	(0.727)	51,820	355	146.0	0.0214	(0.813)	12,477	355	35.1
6	-0.0145	(-0.642)	20,024	354	56.6	0.0158	(1.474)	42,628	354	120.4	0.0809**	(2.020)	51,390	354	145.2	0.0287	(0.953)	12,378	354	35.0
7	0.00764	(0.419)	19,853	353	56.2	0.00972	(0.767)	42,285	353	119.8	0.0298	(1.280)	50,967	353	144.4	0.0230	(0.812)	12,279	353	34.8
8	-0.00465	(-0.231)	19,682	352	55.9	0.00842	(0.978)	41,931	352	119.1	0.0856	(1.406)	50,550	352	143.6	0.0327	(1.417)	12,180	352	34.6
9	0.0385**	(2.166)	19,511	351	55.6	0.00257	(0.193)	41,574	351	118.4	-0.0392	(-0.987)	50,131	351	142.8	-0.0491*	(-1.711)	12,084	351	34.4
10	0.0189	(0.800)	19,340	350	55.3	0.0171	(0.937)	41,221	350	117.8	-0.00356	(-0.116)	49,711	350	142.0	0.0703***	(3.145)	11,989	350	34.3
11	0.00802	(0.465)	19,169	349	54.9	0.0157	(1.413)	40,879	349	117.1	-0.000508	(-0.0162)	49,291	349	141.2	0.0113	(0.371)	11,895	349	34.1
12	0.0229	(1.297)	18,999	348	54.6	0.0211	(1.618)	40,539	348	116.5	-0.0420	(-0.832)	48,870	348	140.4	0.0483**	(2.324)	11,801	348	33.9
24	-0.00902	(-0.341)	16,956	336	50.5	0.0140	(1.386)	36,437	336	108.4	-0.0130	(-0.310)	43,818	336	130.4	0.0995	(1.070)	10,646	336	31.7
36	0.00857	(0.392)	15,000	324	46.3	-0.00659	(-0.581)	32,572	324	100.5	0.0417*	(1.815)	38,930	324	120.2	-0.0150	(-0.497)	9,579	324	29.6
48	0.0361*	(1.950)	13,177	312	42.2	0.0136	(0.918)	28,987	312	92.9	-0.0144	(-0.684)	34,353	312	110.1	-0.560	(-1.099)	8,568	312	27.5
60	-0.00200	(-0.127)	11,494	300	38.3	0.00541	(0.347)	25,661	300	85.5	0.0150	(0.570)	30,018	300	100.1	-0.399	(-1.503)	7,594	300	25.3
72	-0.00585	(-0.334)	10,015	288	34.8	0.0166	(1.226)	22,650	288	78.6	-0.0276	(-0.697)	26,017	288	90.3	-0.539	(-1.424)	6,684	288	23.2
84	-0.0179	(-0.787)	8,665	276	31.4	0.0216*	(1.743)	19,859	276	72.0	-0.0439	(-1.263)	22,335	276	80.9	-1.547	(-0.958)	5,827	276	21.1
96	0.0263	(1.221)	7,404	264	28.0	0.00729	(0.473)	17,207	264	65.2	-0.0567	(-0.805)	18,980	264	71.9	-0.763	(-0.986)	5,036	264	19.1
108	-0.0184	(-0.756)	6,250	252	24.8	0.0314*	(1.875)	14,905	252	59.1	0.0184	(0.185)	15,949	252	63.3	0.681	(1.078)	4,342	252	17.2
120	-0.0261	(-0.822)	5,266	240	21.9	-0.00539	(-0.392)	12,930	240	53.9	-0.0761	(-1.357)	13,230	240	55.1	1.391	(0.991)	3,770	240	15.7

Table XIV: Industry 1 to 4 for Germany

	Industry 1					Industry 2					Industry 3					Industry 4				
Lag	Estimate	t-Stat.	Observations	Months	Avg. no. of firms	Estimate	t-Stat.	Observations	Months	Avg. no. of firms	Estimate	t-Stat.	Observations	Months	Avg. no. of firms	Estimate	t-Stat.	Observations	Months	Avg. no. of firms
1	-0.0304	(-0.871)	8,513	359	23.7	-0.0672***	(-2.967)	12,693	359	35.4	-0.0744***	(-5.407)	45,360	359	126.4	-0.0756***	(-5.107)	47,834	359	133.2
2	0.0125	(0.571)	8,441	358	23.6	-0.0287	(-1.482)	12,580	358	35.1	-0.0138*	(-1.653)	44,987	358	125.7	0.0129	(1.021)	47,462	358	132.6
3	0.0256	(1.081)	8,377	357	23.5	0.0130	(0.805)	12,497	357	35.0	0.0101	(1.134)	44,688	357	125.2	0.00761	(0.716)	47,145	357	132.1
4	0.0211	(0.827)	8,316	356	23.4	0.0272	(1.387)	12,418	356	34.9	0.00924	(0.923)	44,391	356	124.7	0.00962	(0.827)	46,839	356	131.6
5	0.0119	(0.487)	8,254	355	23.3	0.0141	(0.886)	12,344	355	34.8	-0.00383	(-0.465)	44,099	355	124.2	0.00389	(0.356)	46,535	355	131.1
6	0.0124	(0.649)	8,194	354	23.1	0.0259	(1.326)	12,270	354	34.7	0.0105	(0.998)	43,814	354	123.8	0.0163	(1.573)	46,234	354	130.6
7	0.00156	(0.0582)	8,135	353	23.0	-0.00854	(-0.456)	12,191	353	34.5	0.0120	(1.303)	43,537	353	123.3	-0.00296	(-0.290)	45,935	353	130.1
8	0.0120	(0.487)	8,075	352	22.9	0.0178	(1.279)	12,113	352	34.4	-0.00418	(-0.460)	43,259	352	122.9	-0.00259	(-0.270)	45,634	352	129.6
9	0.0677**	(2.502)	8,016	351	22.8	-0.0254	(-1.218)	12,043	351	34.3	0.0207**	(2.089)	42,971	351	122.4	0.00334	(0.340)	45,342	351	129.2
10	-0.0101	(-0.301)	7,959	350	22.7	0.0162	(0.791)	11,976	350	34.2	0.00544	(0.574)	42,686	350	122.0	0.0206**	(2.291)	45,048	350	128.7
11	0.0347*	(1.677)	7,900	349	22.6	0.0207	(1.333)	11,906	349	34.1	0.0154*	(1.815)	42,406	349	121.5	0.0107	(0.990)	44,750	349	128.2
12	0.0318	(1.004)	7,838	348	22.5	0.0118	(0.691)	11,832	348	34.0	0.0208**	(2.431)	42,128	348	121.1	0.0109	(1.070)	44,455	348	127.7
24	0.00311	(0.114)	7,118	336	21.2	0.00220	(0.115)	10,968	336	32.6	-0.00280	(-0.316)	38,780	336	115.4	0.00584	(0.544)	40,902	336	121.7
36	-0.0353	(-1.368)	6,410	324	19.8	-0.0215	(-1.175)	10,123	324	31.2	0.0121	(1.336)	35,494	324	109.5	-0.00570	(-0.672)	37,451	324	115.6
48	-0.0248	(-1.012)	5,763	312	18.5	0.0294	(1.438)	9,277	312	29.7	0.00687	(0.586)	32,317	312	103.6	0.0113	(1.279)	34,119	312	109.4
60	-0.000576	(-0.0259)	5,145	300	17.2	0.00548	(0.237)	8,491	300	28.3	-0.00375	(-0.285)	29,246	300	97.5	0.00553	(0.560)	30,984	300	103.3
72	0.00199	(0.0663)	4,553	288	15.8	0.00382	(0.237)	7,743	288	26.9	0.0140	(0.863)	26,342	288	91.5	0.0129	(1.136)	28,031	288	97.3
84	0.0233	(0.947)	4,006	276	14.5	0.0605***	(2.614)	7,020	276	25.4	0.00480	(0.403)	23,545	276	85.3	0.0141	(1.014)	25,253	276	91.5
96	0.0103	(0.499)	3,489	264	13.2	-0.00446	(-0.150)	6,347	264	24.0	0.00559	(0.354)	20,909	264	79.2	-0.00121	(-0.101)	22,596	264	85.6
108	-0.0108	(-0.357)	3,055	252	12.1	-0.00368	(-0.106)	5,716	252	22.7	0.0288**	(2.033)	18,515	252	73.5	0.0311**	(1.991)	20,050	252	79.6
120	0.0366	(0.964)	2,702	240	11.3	-0.0106	(-0.267)	5,189	240	21.6	-0.000903	(-0.0733)	16,360	240	68.2	-0.0115	(-0.912)	17,658	240	73.6

Table XV: Industry 5 to 8 for Germany

	Industry 5					Industry 6					Industry 7					Industry 8				
Lag	Estimate	t-Stat.	Obser-vations	Months	Avg. no. of firms	Estimate	t-Stat.	Obser-vations	Months	Avg. no. of firms	Estimate	t-Stat.	Obser-vations	Months	Avg. no. of firms	Estimate	t-Stat.	Obser-vations	Months	Avg. no. of firms
1	-0.0439**	(-2.210)	13,154	359	36.6	-0.0635***	(-3.646)	34,921	359	97.3	0.0303	(0.460)	38,443	337	114.1	-0.126	(-1.517)	10,058	359	28.0
2	0.00126	(0.0448)	13,065	358	36.5	0.00772	(0.710)	34,558	358	96.5	-0.444	(-1.074)	38,144	336	113.5	0.900	(1.261)	9,952	358	27.8
3	-0.00620	(-0.177)	12,978	357	36.4	-0.00344	(-0.282)	34,270	357	96.0	-0.251	(-0.804)	37,856	335	113.0	-0.250	(-1.444)	9,875	357	27.7
4	0.0361	(0.807)	12,891	356	36.2	-0.0146	(-1.032)	33,990	356	95.5	-0.0268	(-0.481)	37,568	334	112.5	-0.687	(-1.141)	9,798	356	27.5
5	0.0231	(0.843)	12,804	355	36.1	0.00750	(0.559)	33,719	355	95.0	0.193	(1.202)	37,278	333	111.9	-0.896	(-1.368)	9,723	355	27.4
6	-0.0207	(-0.587)	12,718	354	35.9	0.0138	(1.152)	33,455	354	94.5	0.157	(1.109)	36,987	332	111.4	1.205	(1.225)	9,650	354	27.3
7	0.0743	(1.337)	12,632	353	35.8	-0.00167	(-0.111)	33,188	353	94.0	-0.481	(-0.994)	36,702	331	110.9	0.241	(0.462)	9,577	353	27.1
8	0.0118	(0.480)	12,546	352	35.6	0.00939	(0.986)	32,911	352	93.5	0.339	(1.055)	36,422	330	110.4	0.0728	(0.111)	9,504	352	27.0
9	0.0394	(1.313)	12,460	351	35.5	-0.00442	(-0.304)	32,630	351	93.0	-0.329	(-0.950)	36,140	329	109.8	0.725	(1.269)	9,434	351	26.9
10	0.0165	(0.515)	12,374	350	35.4	0.0297*	(1.679)	32,353	350	92.4	0.301	(0.949)	35,856	328	109.3	-0.0258	(-0.232)	9,365	350	26.8
11	-0.0501**	(-2.045)	12,288	349	35.2	0.0146	(1.266)	32,089	349	91.9	0.665	(1.031)	35,572	327	108.8	-0.311	(-0.857)	9,297	349	26.6
12	0.00440	(0.138)	12,203	348	35.1	0.0268*	(1.837)	31,825	348	91.5	-0.424	(-0.715)	35,289	326	108.2	0.247	(1.016)	9,229	348	26.5
24	-0.0398	(-1.246)	11,174	336	33.3	0.00989	(0.909)	28,644	336	85.3	0.378	(1.019)	31,897	314	101.6	-0.339	(-0.646)	8,386	336	25.0
36	-0.0115	(-0.423)	10,162	324	31.4	-0.00993	(-0.735)	25,663	324	79.2	-0.334	(-0.861)	28,571	302	94.6	0.282	(0.769)	7,603	324	23.5
48	-0.00511	(-0.0874)	9,175	312	29.4	0.00920	(0.802)	22,864	312	73.3	0.544	(1.069)	25,397	290	87.6	-0.833	(-1.547)	6,858	312	22.0
60	0.00752	(0.267)	8,224	300	27.4	0.00176	(0.101)	20,244	300	67.5	-1.991	(-1.018)	22,351	278	80.4	-0.209	(-0.851)	6,135	300	20.5
72	-0.0492	(-1.088)	7,333	288	25.5	0.00662	(0.569)	17,852	288	62.0	0.820	(0.978)	19,470	266	73.2	-0.585	(-1.519)	5,441	288	18.9
84	-0.0417	(-1.097)	6,479	276	23.5	0.00154	(0.104)	15,607	276	56.5	-0.0506	(-0.326)	16,773	254	66.0	-1.544	(-0.955)	4,772	276	17.3
96	0.00934	(0.407)	5,637	264	21.4	0.0145	(0.900)	13,473	264	51.0	-0.179	(-1.131)	14,254	242	58.9	-0.759	(-0.981)	4,142	264	15.7
108	-0.00444	(-0.114)	4,834	252	19.2	0.0393	(1.581)	11,641	252	46.2	-0.441	(-0.818)	11,936	230	51.9	0.674	(1.066)	3,598	252	14.3
120	-0.00439	(-0.129)	4,108	240	17.1	-0.0147	(-0.905)	10,070	240	42.0	0.0666	(0.348)	9,859	206	47.9	1.397	(0.996)	3,159	240	13.2

Table XVI: Industry 1 to 4 for Sweden

	Industry 1					Industry 2					Industry 3					Industry 4				
Lag	Estimate	t-Stat.	Obser-vations	Months	Avg. no. of firms	Estimate	t-Stat.	Obser-vations	Months	Avg. no. of firms	Estimate	t-Stat.	Obser-vations	Months	Avg. no. of firms	Estimate	t-Stat.	Obser-vations	Months	Avg. no. of firms
1	-0.0392	(-0.601)	2,749	289	9.5	-0.0720***	(-2.851)	5,435	359	15.1	-0.0825***	(-5.088)	19,455	359	54.2	-0.0489**	(-2.227)	11,662	359	32.5
2	-0.129*	(-1.827)	2,721	288	9.4	0.0108	(0.358)	5,382	358	15.0	0.00588	(0.299)	19,280	358	53.9	0.0336	(1.161)	11,547	358	32.3
3	0.00459	(0.0798)	2,693	287	9.4	0.00130	(0.0432)	5,333	357	14.9	0.0305**	(2.044)	19,122	357	53.6	0.0170	(0.628)	11,437	357	32.0
4	0.00330	(0.0632)	2,665	286	9.3	-0.0207	(-0.723)	5,285	356	14.8	0.000802	(0.0488)	18,969	356	53.3	0.00267	(0.0948)	11,326	356	31.8
5	0.0109	(0.207)	2,637	285	9.3	0.00996	(0.425)	5,237	355	14.8	0.0176	(1.138)	18,815	355	53.0	0.0403	(1.406)	11,217	355	31.6
6	-0.0304	(-0.586)	2,609	284	9.2	0.0362*	(1.877)	5,190	354	14.7	0.0361**	(2.032)	18,659	354	52.7	0.0108	(0.383)	11,108	354	31.4
7	-0.0321	(-0.750)	2,581	283	9.1	-0.0137	(-0.466)	5,144	353	14.6	-0.00907	(-0.399)	18,503	353	52.4	0.0537	(1.458)	10,997	353	31.2
8	0.00339	(0.0714)	2,553	282	9.1	0.00125	(0.0492)	5,098	352	14.5	0.00914	(0.766)	18,348	352	52.1	0.0128	(0.531)	10,890	352	30.9
9	-0.0876	(-1.584)	2,525	281	9.0	0.0111	(0.399)	5,052	351	14.4	0.0104	(0.644)	18,195	351	51.8	0.0205	(0.843)	10,785	351	30.7
10	0.109**	(2.217)	2,497	280	8.9	0.0491*	(1.781)	5,006	350	14.3	-0.00383	(-0.197)	18,044	350	51.6	0.0391	(1.084)	10,679	350	30.5
11	0.0513	(0.889)	2,469	279	8.8	0.0162	(0.580)	4,960	349	14.2	-0.0206	(-0.905)	17,893	349	51.3	0.0251	(1.188)	10,573	349	30.3
12	0.0236	(0.424)	2,441	278	8.8	0.0347	(1.444)	4,913	348	14.1	0.0342**	(2.444)	17,737	348	51.0	0.0385	(1.257)	10,465	348	30.1
24	-1.295	(-1.204)	2,105	266	7.9	0.0226	(0.890)	4,356	336	13.0	0.0455***	(2.651)	15,908	336	47.3	0.0570**	(1.984)	9,167	336	27.3
36	-3,723	(-1.025)	1,787	254	7.0	0.0358	(1.616)	3,812	324	11.8	0.0505***	(2.654)	14,169	324	43.7	0.00221	(0.0698)	7,958	324	24.6
48	17,555	(1.026)	1,493	242	6.2	0.0431	(1.057)	3,315	312	10.6	-0.00656	(-0.367)	12,553	312	40.2	0.0245	(0.553)	6,860	312	22.0
60	3,332	(1.004)	1,219	217	5.6	-0.0627	(-1.645)	2,833	300	9.4	0.0142	(0.788)	11,043	300	36.8	0.0210	(0.519)	5,863	300	19.5
72	-1.026	(-1.018)	973	181	5.4	-0.0541	(-1.368)	2,402	288	8.3	0.0274	(1.550)	9,694	288	33.7	-0.00704	(-0.166)	4,996	288	17.3
84	0.109	(1.040)	752	142	5.3	-0.00719	(-0.119)	1,989	276	7.2	-0.0375	(-1.444)	8,479	276	30.7	0.0353	(0.810)	4,188	276	15.2
96	0.0442	(0.347)	560	117	4.8	0.0511	(1.082)	1,648	264	6.2	0.00868	(0.578)	7,419	264	28.1	0.0365	(0.983)	3,453	264	13.1
108	-0.217	(-0.982)	408	93	4.4	0.0485	(0.426)	1,387	252	5.5	0.00530	(0.329)	6,502	252	25.8	-0.0192	(-0.434)	2,821	252	11.2
120	-0.0760	(-0.636)	302	71	4.3	-0.0416	(-0.359)	1,205	237	5.1	0.0357*	(1.801)	5,716	240	23.8	0.0976**	(1.988)	2,369	240	9.9

Table XVII: Industry 5 to 8 for Sweden

Industry 5

Lag	Estimate	t-Stat.	Obser-vations	Months	Avg. no. of firms
1	-0.0537	(-1.337)	7,732	359	21.5
2	0.00995	(0.332)	7,646	358	21.4
3	-0.0127	(-0.232)	7,561	357	21.2
4	0.0709	(1.430)	7,476	356	21.0
5	-0.0670	(-0.990)	7,391	355	20.8
6	0.0189	(0.613)	7,306	354	20.6
7	0.0302	(0.800)	7,221	353	20.5
8	0.0259	(0.710)	7,136	352	20.3
9	0.0531	(1.428)	7,051	351	20.1
10	0.0341	(0.826)	6,966	350	19.9
11	0.00512	(0.141)	6,881	349	19.7
12	-0.0122	(-0.332)	6,796	348	19.5
24	-0.0104	(-0.229)	5,782	336	17.2
36	0.137**	(2.137)	4,838	324	14.9
48	0.0132	(0.138)	4,002	312	12.8
60	-0.0735	(-0.617)	3,270	296	11.0
72	-0.00997	(-0.0685)	2,682	272	9.9
84	0.407	(1.435)	2,186	248	8.8
96	-805.6	(-1.027)	1,767	224	7.9
108	-2,245	(-1.018)	1,416	191	7.4
120	-491.2	(-1.035)	1,158	155	7.5

Industry 6

Lag	Estimate	t-Stat.	Obser-vations	Months	Avg. no. of firms
1	-0.0744**	(-2.168)	9,600	359	26.7
2	0.0242	(0.720)	9,501	358	26.5
3	-0.0207	(-0.590)	9,418	357	26.4
4	0.0171	(0.524)	9,336	356	26.2
5	0.00182	(0.0547)	9,252	355	26.1
6	-0.0242	(-0.625)	9,173	354	25.9
7	0.0257	(0.527)	9,097	353	25.8
8	-0.0383	(-1.523)	9,020	352	25.6
9	0.0360	(1.056)	8,944	351	25.5
10	-0.00391	(-0.0830)	8,868	350	25.3
11	0.0501	(1.331)	8,790	349	25.2
12	-0.0350	(-0.940)	8,714	348	25.0
24	0.0511	(1.308)	7,793	336	23.2
36	0.0150	(0.408)	6,909	324	21.3
48	0.125*	(1.833)	6,123	312	19.6
60	-0.0279	(-0.443)	5,417	300	18.1
72	0.132	(1.123)	4,798	288	16.7
84	-0.0741	(-1.159)	4,252	276	15.4
96	0.00191	(0.0402)	3,734	264	14.1
108	-0.0355	(-0.927)	3,264	252	13.0
120	-0.0953	(-1.179)	2,860	235	12.2

Industry 7

Lag	Estimate	t-Stat.	Obser-vations	Months	Avg. no. of firms
1	-0.0107	(-0.0716)	15,116	359	42.1
2	1.236	(1.126)	14,970	358	41.8
3	0.0864	(0.356)	14,828	357	41.5
4	0.150	(0.544)	14,684	356	41.2
5	0.186	(0.359)	14,542	355	41.0
6	0.893	(1.188)	14,403	354	40.7
7	0.634	(0.940)	14,265	353	40.4
8	-1.305	(-0.847)	14,128	352	40.1
9	2.668	(1.172)	13,991	351	39.9
10	-2.007	(-1.384)	13,855	350	39.6
11	1.560	(1.144)	13,719	349	39.3
12	-1.504	(-1.199)	13,581	348	39.0
24	0.811	(1.085)	11,921	336	35.5
36	1.243	(0.933)	10,359	324	32.0
48	2.469	(1.045)	8,956	312	28.7
60	-0.0424	(-0.379)	7,667	300	25.6
72	1.487	(1.031)	6,547	288	22.7
84	-0.0292	(-0.256)	5,562	276	20.2
96	0.332	(0.913)	4,726	264	17.9
108	0.0338	(0.137)	4,013	252	15.9
120	0.107	(0.922)	3,371	240	14.0

Industry 8

Lag	Estimate	t-Stat.	Obser-vations	Months	Avg. no. of firms
1	-0.0207	(-0.341)	2,858	229	12.5
2	0.0562	(0.892)	2,832	228	12.4
3	0.0872	(1.585)	2,806	227	12.4
4	0.195*	(1.908)	2,780	226	12.3
5	0.0619	(1.351)	2,754	225	12.2
6	0.107***	(2.604)	2,728	224	12.2
7	0.0406	(1.140)	2,702	223	12.1
8	0.0445	(0.894)	2,676	222	12.1
9	0.0393	(0.894)	2,650	221	12.0
10	0.122***	(4.296)	2,624	220	11.9
11	0.0103	(0.222)	2,598	219	11.9
12	0.0602	(1.446)	2,572	218	11.8
24	0.138***	(2.813)	2,260	206	11.0
36	0.00184	(0.0289)	1,976	194	10.2
48	0.0201	(0.502)	1,710	182	9.4
60	0.0946*	(1.672)	1,459	168	8.7
72	0.00582	(0.134)	1,243	156	8.0
84	-0.00340	(-0.0973)	1,055	144	7.3
96	-0.0221	(-0.337)	894	132	6.8
108	-0.0207	(-0.319)	744	120	6.2
120	-0.0284	(-0.367)	611	108	5.7

Table XVIII: All firms without January observations

	Germany and Sweden					Germany					Sweden				
Lag	Estimate	t-Stat.	Obser-vations	Months	Avg. no. of firms	Estimate	t-Stat.	Obser-vations	Months	Avg. no. of firms	Estimate	t-Stat.	Obser-vations	Months	Avg. no. of firms
1	-0.0487***	(-4.411)	243,267	300	810.9	-0.0525***	(-4.211)	179,330	300	597.8	-0.0338**	(-2.534)	63,937	300	213.1
2	0.0113	(1.631)	240,955	299	805.9	0.00658	(0.927)	177,723	299	594.4	0.0400***	(2.804)	63,232	299	211.5
3	0.0200**	(2.401)	238,976	298	801.9	0.0149*	(1.754)	176,353	298	591.8	0.0386***	(4.368)	62,623	298	210.1
4	0.0123	(1.437)	236,967	297	797.9	0.0129	(1.613)	174,998	297	589.2	0.0171	(1.307)	61,969	297	208.6
5	0.00989	(1.198)	234,997	296	793.9	0.0115	(1.340)	173,621	296	586.6	0.0275**	(2.446)	61,376	296	207.4
6	0.0267***	(3.347)	233,038	295	790.0	0.0259***	(3.049)	172,292	295	584.0	0.0422***	(3.603)	60,746	295	205.9
7	0.00962	(1.612)	231,186	294	786.3	0.00399	(0.661)	171,046	294	581.8	0.0240**	(2.340)	60,140	294	204.6
8	0.00442	(0.700)	229,333	293	782.7	0.00887	(1.337)	169,804	293	579.5	0.0107	(1.479)	59,529	293	203.2
9	0.0155**	(2.090)	227,382	292	778.7	0.0113	(1.296)	168,477	292	577.0	0.0246**	(2.554)	58,905	292	201.7
10	0.0158**	(2.024)	225,551	291	775.1	0.0188***	(2.903)	167,235	291	574.7	0.0111	(1.209)	58,316	291	200.4
11	0.0191**	(2.490)	223,569	290	770.9	0.0190**	(2.547)	165,898	290	572.1	0.0198*	(1.814)	57,671	290	198.9
12	0.0264***	(4.107)	244,569	319	766.7	0.0223***	(3.197)	181,540	319	569.1	0.0372***	(3.809)	63,029	319	197.6
24	0.0166***	(3.357)	220,959	308	717.4	0.0100**	(1.997)	165,517	308	537.4	0.0420***	(5.086)	55,442	308	180.0
36	0.00633	(1.119)	198,305	297	667.7	0.00154	(0.252)	150,041	297	505.2	0.0321**	(2.508)	48,264	297	162.5
48	0.00740	(1.463)	177,074	286	619.1	0.00703	(1.096)	135,280	286	473.0	0.0242*	(1.715)	41,794	286	146.1
60	0.00617	(0.888)	157,095	275	571.3	0.00416	(0.492)	121,218	275	440.8	0.0301***	(3.070)	35,877	275	130.5
72	0.0138**	(2.154)	138,821	264	525.8	0.0103	(1.369)	108,053	264	409.3	0.0180*	(1.953)	30,768	264	116.5
84	0.0128**	(2.441)	121,858	253	481.7	0.00873	(1.505)	95,623	253	378.0	0.00844	(0.852)	26,235	253	103.7
96	0.00928	(1.277)	106,166	242	438.7	0.00964	(1.236)	83,867	242	346.6	0.00564	(0.495)	22,299	242	92.1
108	0.0192***	(3.188)	92,094	231	398.7	0.0204***	(3.165)	73,168	231	316.7	0.0258**	(2.001)	18,926	231	81.9
120	-0.00157	(-0.213)	79,877	220	363.1	-0.00427	(-0.572)	63,677	220	289.4	0.0160	(1.425)	16,200	220	73.6

Table XIX: Comparison of excluding January to excluding other months

	Germany and Sweden			Germany			Sweden		
	No. of significantly positive estimates at annual lags	Average of all estimates at annual lags	Average t-Stat. of all estimates at annual lags	No. of significantly positive estimates at annual lags	Average of all estimates at annual lags	Average t-Stat. of all estimates at annual lags	No. of significantly positive estimates at annual lags	Average of all estimates at annual lags	Average t-Stat. of all estimates at annual lags
All observations	7	1.25%	2.31	5	0.93%	1.61	8	2.41%	2.46
Excluding January	5	1.16%	2.02	3	0.90%	1.49	7	2.39%	2.29
Excluding other months									
Average	6.5	1.27%	2.23	4.5	0.93%	1.55	6.6	2.42%	2.36
Median	6.0	1.28%	2.22	5.0	0.91%	1.54	7.0	2.44%	2.38
Excluding February	8	1.37%	2.37	6	1.02%	1.63	6	2.42%	2.38
Excluding March	8	1.37%	2.13	4	0.89%	1.42	7	2.54%	2.44
Excluding April	6	1.16%	2.05	4	0.86%	1.50	6	2.17%	2.17
Excluding May	6	1.31%	2.28	5	1.05%	1.61	8	2.72%	2.55
Excluding June	7	1.28%	2.22	4	0.96%	1.54	7	2.48%	2.37
Excluding July	6	1.26%	2.38	5	0.90%	1.67	6	2.48%	2.40
Excluding August	7	1.33%	2.42	5	1.02%	1.78	7	2.40%	2.41
Excluding September	7	1.30%	2.26	3	0.93%	1.43	7	2.51%	2.44
Excluding October	6	1.17%	2.16	5	0.89%	1.55	7	2.08%	2.24
Excluding November	5	1.24%	2.16	5	0.91%	1.51	6	2.44%	2.32
Excluding December	6	1.17%	2.10	4	0.80%	1.46	6	2.34%	2.20

Table XX: First half of the time period

	Germany and Sweden					Germany					Sweden				
Lag	Estimate	t-Stat.	Obser-vations	Months	Avg. no. of firms	Estimate	t-Stat.	Obser-vations	Months	Avg. no. of firms	Estimate	t-Stat.	Obser-vations	Months	Avg. no. of firms
1	-0.0277*	(-1.915)	77,662	179	433.9	-0.0159	(-1.100)	58,935	179	329.2	-0.0662***	(-3.046)	18,727	179	104.6
2	0.0120	(1.052)	76,104	178	427.6	0.00872	(0.912)	57,768	178	324.5	0.0527**	(2.434)	18,336	178	103.0
3	0.0211*	(1.842)	74,860	177	422.9	0.0182*	(1.834)	56,874	177	321.3	0.0274*	(1.726)	17,986	177	101.6
4	-1.65e-05	(-0.00150)	73,651	176	418.5	0.00612	(0.650)	56,007	176	318.2	-0.0191	(-1.016)	17,644	176	100.3
5	-0.00227	(-0.169)	72,471	175	414.1	0.00628	(0.479)	55,154	175	315.2	0.0144	(0.788)	17,317	175	99.0
6	0.0225*	(1.956)	71,327	174	409.9	0.0172	(1.511)	54,338	174	312.3	0.0459***	(2.730)	16,989	174	97.6
7	0.00224	(0.271)	70,226	173	405.9	-0.00119	(-0.167)	53,561	173	309.6	0.0233	(1.605)	16,665	173	96.3
8	0.00933	(1.017)	69,122	172	401.9	0.0123	(1.598)	52,778	172	306.8	0.00997	(0.773)	16,344	172	95.0
9	0.0222**	(2.251)	68,025	171	397.8	0.0108	(0.862)	51,997	171	304.1	0.0190	(1.328)	16,028	171	93.7
10	0.0149	(1.154)	66,974	170	394.0	0.0195**	(2.026)	51,254	170	301.5	0.00170	(0.0861)	15,720	170	92.5
11	0.0216*	(1.817)	65,955	169	390.3	0.0209*	(1.809)	50,546	169	299.1	0.0140	(0.693)	15,409	169	91.2
12	0.0341***	(3.797)	64,973	168	386.7	0.0336***	(3.300)	49,831	168	296.6	0.0435***	(3.373)	15,142	168	90.1
24	0.0239***	(2.982)	54,551	156	349.7	0.0135	(1.475)	42,452	156	272.1	0.0536***	(4.218)	12,099	156	77.6
36	0.0112	(1.296)	45,516	144	316.1	0.00335	(0.423)	36,170	144	251.2	0.0162	(0.639)	9,346	144	64.9
48	0.0138	(1.526)	37,715	132	285.7	0.0157	(1.196)	30,520	132	231.2	0.0252	(0.740)	7,195	132	54.5
60	0.0222	(1.570)	30,893	120	257.4	0.0239	(1.340)	25,341	120	211.2	0.0366**	(2.020)	5,552	120	46.3
72	0.0355***	(3.066)	24,889	108	230.5	0.0302**	(2.215)	20,738	108	192.0	0.0209	(1.180)	4,151	108	38.4
84	0.0257**	(2.587)	19,650	96	204.7	0.0258**	(2.150)	16,566	96	172.6	-0.00570	(-0.298)	3,084	96	32.1
96	0.00439	(0.262)	15,367	84	182.9	0.00906	(0.526)	13,091	84	155.8	-0.00255	(-0.105)	2,276	84	27.1
108	0.0149	(1.146)	11,910	72	165.4	0.0127	(0.921)	10,330	72	143.5	0.0482*	(1.801)	1,580	72	21.9
120	-0.000413	(-0.0327)	8,800	60	146.7	0.00506	(0.423)	7,628	60	127.1	0.0117	(0.435)	1,172	60	19.5

Table XXI: Second half of the time period

	Germany and Sweden					Germany					Sweden				
Lag	Estimate	t-Stat.	Obser-vations	Months	Avg. no. of firms	Estimate	t-Stat.	Obser-vations	Months	Avg. no. of firms	Estimate	t-Stat.	Obser-vations	Months	Avg. no. of firms
1	-0.0830***	(-7.283)	212,042	179	1184.6	-0.0945***	(-7.197)	154,733	179	864.4	-0.0413***	(-3.469)	57,309	179	320.2
2	0.000710	(0.120)	209,932	178	1179.4	0.00224	(0.284)	153,251	178	861.0	0.0121	(1.004)	56,681	178	318.4
3	0.00755	(0.952)	207,905	177	1174.6	0.00243	(0.285)	151,837	177	857.8	0.0223**	(2.520)	56,068	177	316.8
4	0.0107*	(1.933)	205,892	176	1169.8	0.00656	(0.904)	150,433	176	854.7	0.0326***	(4.558)	55,459	176	315.1
5	0.00860*	(1.962)	203,891	175	1165.1	0.00696	(1.358)	149,043	175	851.7	0.0185**	(2.501)	54,848	175	313.4
6	0.0194***	(2.708)	201,904	174	1160.4	0.0210**	(2.427)	147,661	174	848.6	0.0192**	(2.055)	54,243	174	311.7
7	0.00431	(0.793)	199,934	173	1155.7	0.00305	(0.487)	146,294	173	845.6	0.0165*	(1.724)	53,640	173	310.1
8	-0.00244	(-0.416)	197,972	172	1151.0	-0.000434	(-0.0555)	144,931	172	842.6	0.00127	(0.208)	53,041	172	308.4
9	0.00647	(0.932)	196,019	171	1146.3	0.00713	(0.832)	143,572	171	839.6	0.0125	(1.298)	52,447	171	306.7
10	0.00582	(0.785)	194,066	170	1141.6	0.00879	(1.093)	142,210	170	836.5	0.00247	(0.303)	51,856	170	305.0
11	0.00901*	(1.850)	192,115	169	1136.8	0.00679	(1.323)	140,847	169	833.4	0.0123	(1.530)	51,268	169	303.4
12	0.0235***	(2.760)	190,174	168	1132.0	0.0189**	(2.198)	139,493	168	830.3	0.0337***	(2.743)	50,681	168	301.7
24	0.0101*	(1.921)	167,266	156	1072.2	0.00312	(0.607)	123,538	156	791.9	0.0457***	(4.581)	43,728	156	280.3
36	0.0114*	(1.817)	145,986	144	1013.8	0.00624	(0.797)	108,690	144	754.8	0.0490***	(6.318)	37,296	144	259.0
48	0.00561	(1.040)	126,336	132	957.1	0.00347	(0.530)	94,790	132	718.1	0.0196***	(2.818)	31,546	132	239.0
60	-0.0100**	(-2.030)	108,097	120	900.8	-0.0164***	(-3.384)	81,759	120	681.3	0.0174*	(1.736)	26,338	120	219.5
72	0.00573	(0.891)	91,550	108	847.7	0.00582	(0.766)	69,712	108	645.5	0.0106	(1.112)	21,838	108	202.2
84	0.00525	(1.052)	76,220	96	794.0	0.00101	(0.179)	58,409	96	608.4	0.0337***	(3.218)	17,811	96	185.5
96	0.0105	(1.171)	62,101	84	739.3	0.0102	(0.845)	47,826	84	569.4	0.0169**	(2.077)	14,275	84	169.9
108	0.00906	(1.213)	49,634	72	689.4	0.00600	(0.616)	38,374	72	533.0	0.0275***	(3.094)	11,260	72	156.4
120	-0.000628	(-0.0430)	39,007	60	650.1	-0.00262	(-0.166)	30,173	60	502.9	0.0133	(1.394)	8,834	60	147.2

Appendix B
Figures

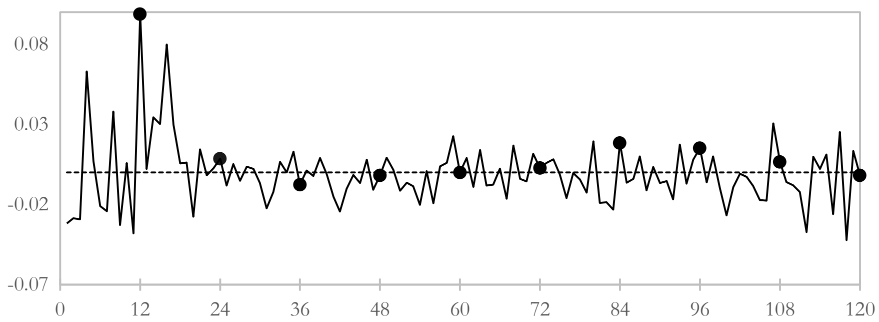
All figures show the time-series averages of the coefficient estimates of the monthly univariate Fama MacBeth (1973) regressions $r_{i,t} = a_{k,t} + b_{k,t} r_{i,t-k} + e_{i,t}$, which are calculated for each month *t* and lag *k*. The variable $r_{i,t}$ is the return of stock *i* in month *t* and $r_{i,t-k}$ the return of stock *i* in month *t* - *k*. The regression is calculated for every month *t* from February 1986 through December 2015 (359 months), and for lag *k* values 1 – 120. Coefficient estimates are plotted for lags 1 to 120 and separately for different samples: Germany and Sweden combined, Germany only and Sweden only.

Appendix B includes all figures that are not reported in the main section, i.e. for the following subsets: (1) value, growth, and other forms, each for Germany and for Sweden (2) high, middle, and low profitability firms, each for Germany and Sweden combined, for Germany, and for Sweden, (3) the eight industries, each for Germany and Sweden combined, for Germany, and for Sweden.

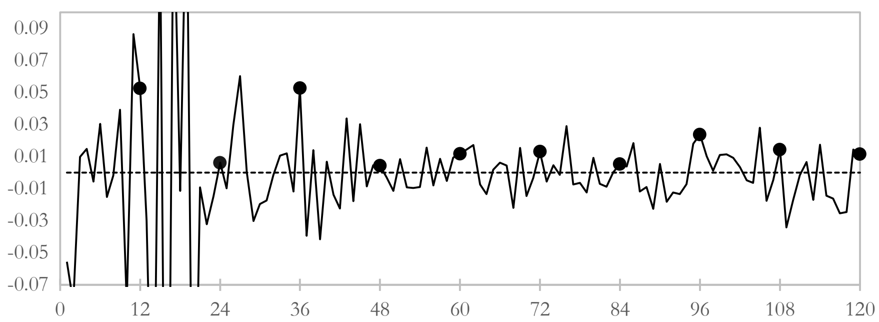
Note that the X-axis always displays lags in months and the Y-axis the level of the coefficient estimates.

Figure I: Top 30%, bottom 30%, and middle 40% book-to-market for (B) Germany and (C) Sweden

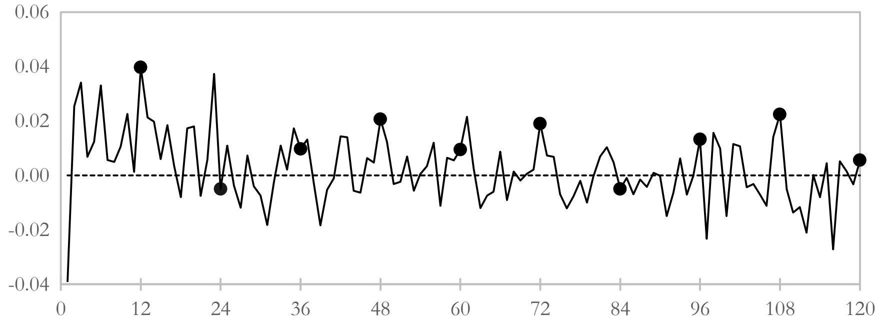
Panel B-I. **Germany: Top 30% book-to-market**



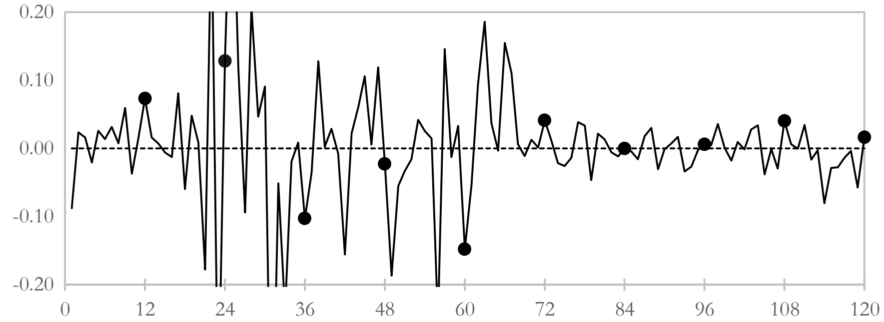
Panel B-II. **Germany: Bottom 30% book-to-market**



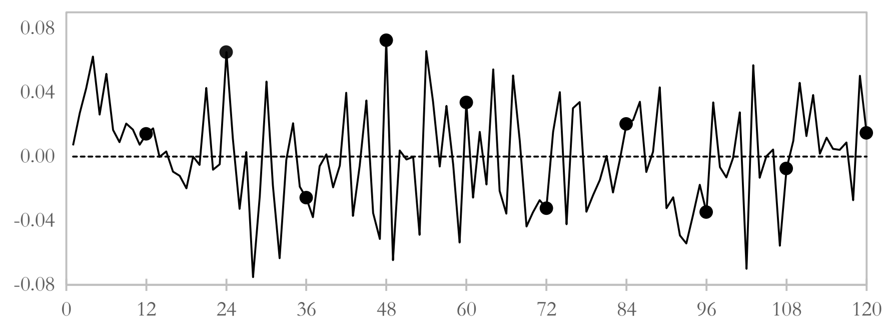
Panel B-III. **Germany: Middle 40% book-to-market**



Panel C-I. **Sweden: Top 30% book-to-market**



Panel C-II. **Sweden: Bottom 30% book-to-market**



Panel C-III. **Sweden: Middle 40% book-to-market**

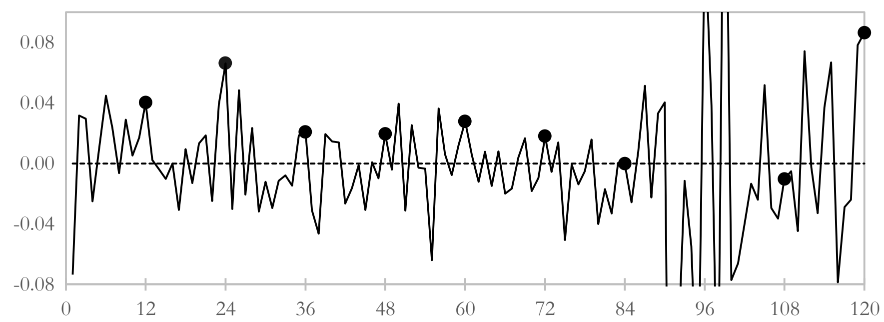
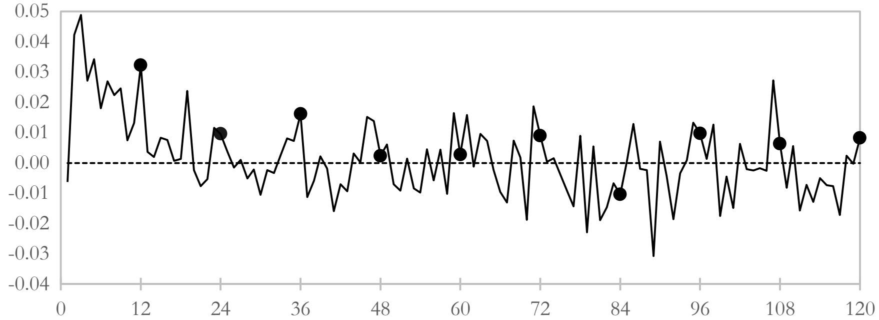
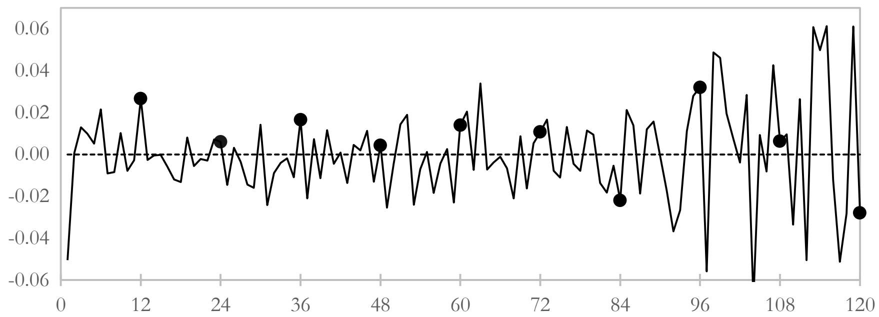


Figure II: High, low, and middle profitability firms for (A) Germany and Sweden

Panel A-I. **Germany and Sweden: High Profitability Firms**



Panel A-II. **Germany and Sweden: Low Profitability Firms**



Panel A-III. **Germany and Sweden: Middle Profitability Firms**

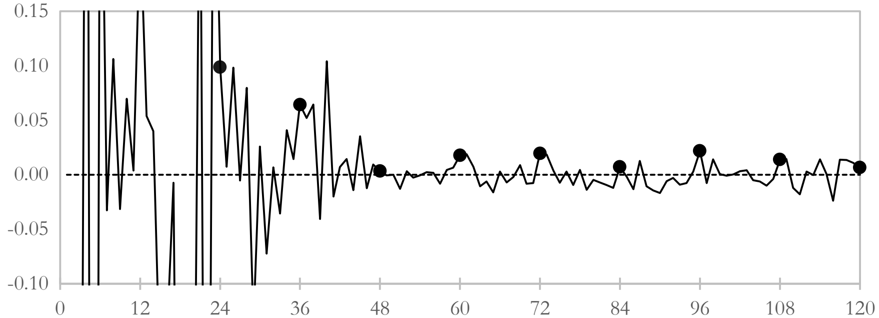
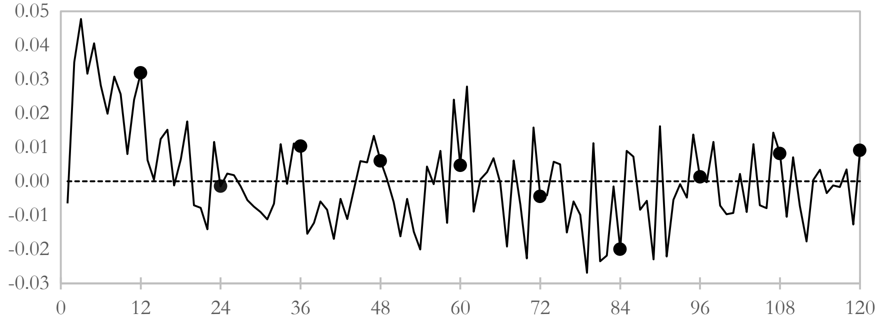
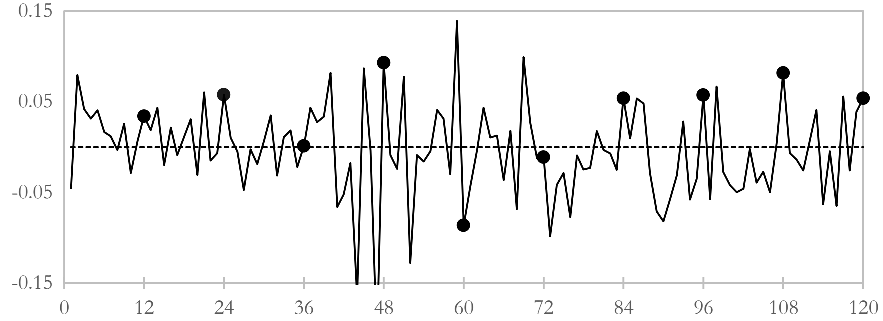


Figure III: High, low, and middle profitability firms for (B) Germany and (C) Sweden

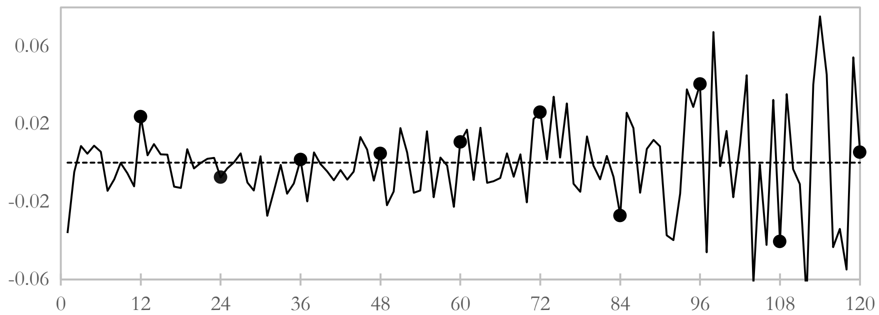
Panel B-I. **Germany: High Profitability Firms**



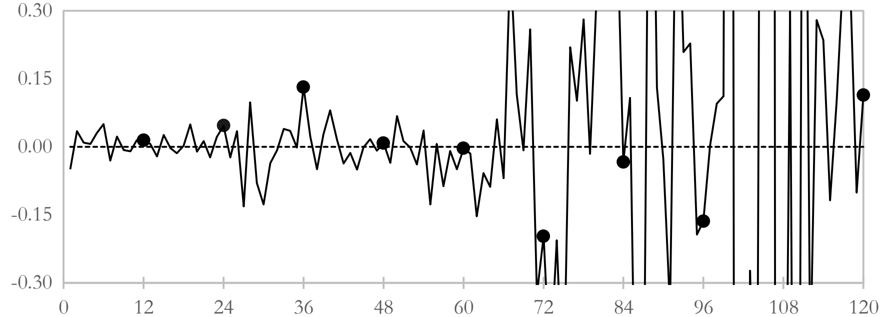
Panel C-I. **Sweden: High Profitability Firms**



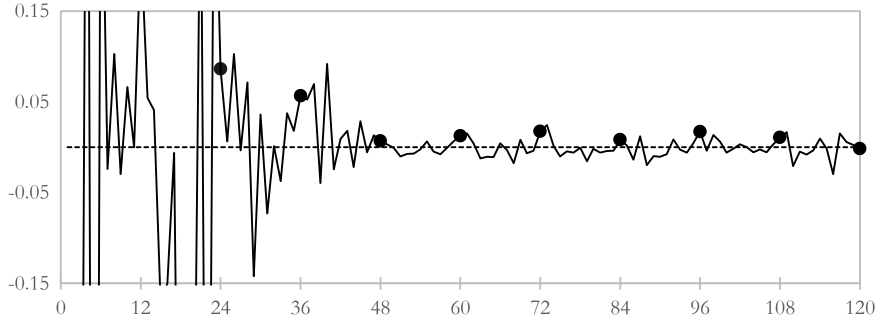
Panel B-II. **Germany: Low Profitability Firms**



Panel C-II. **Sweden: Low Profitability Firms**



Panel B-III. **Germany: Middle Profitability Firms**



Panel C-III. **Sweden: Middle Profitability Firms**

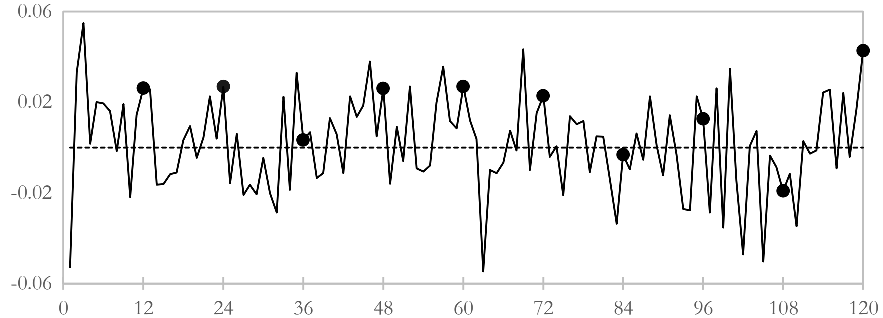
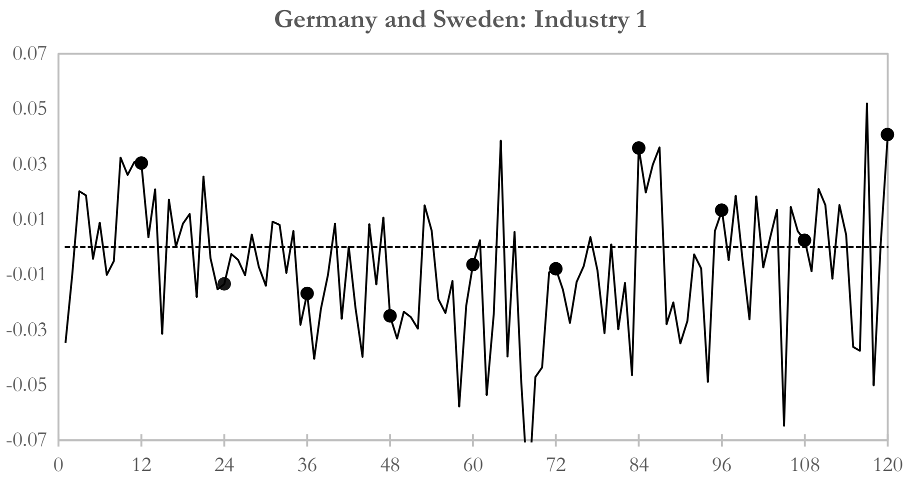
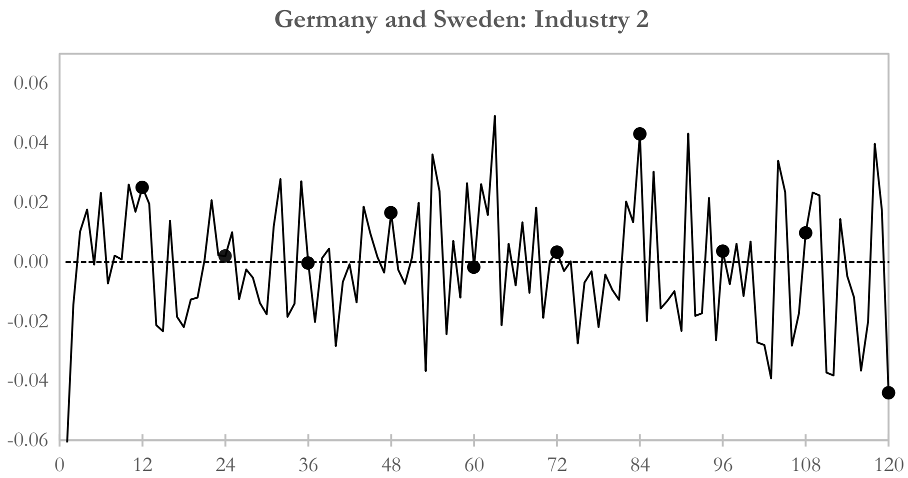
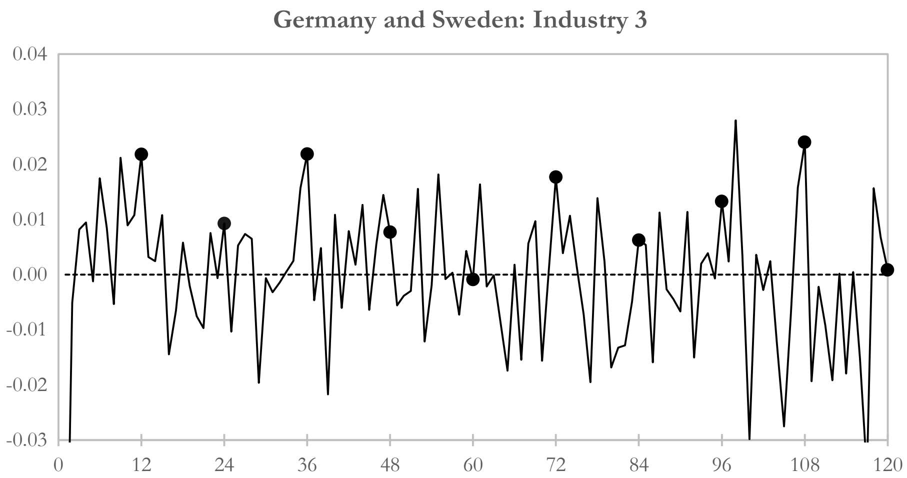


Figure IV: Industries 1 to 4 for Germany and Sweden







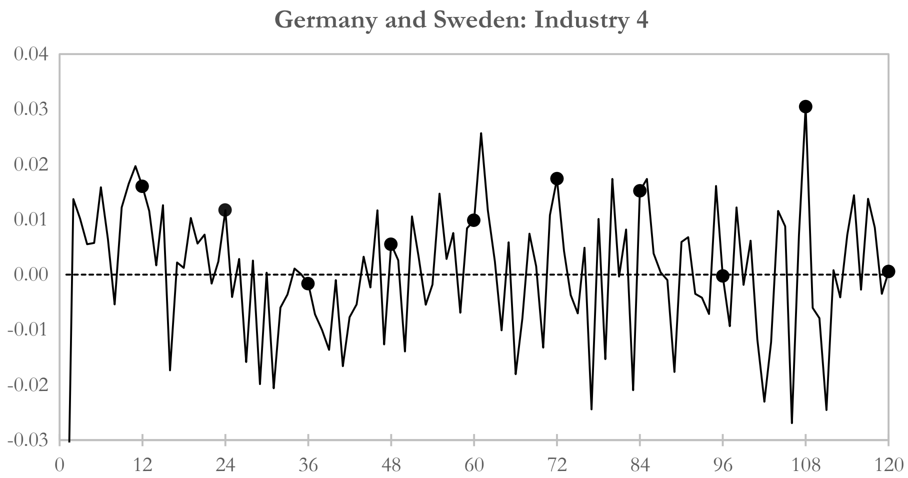


Figure V: Industries 5 to 8 for Germany and Sweden

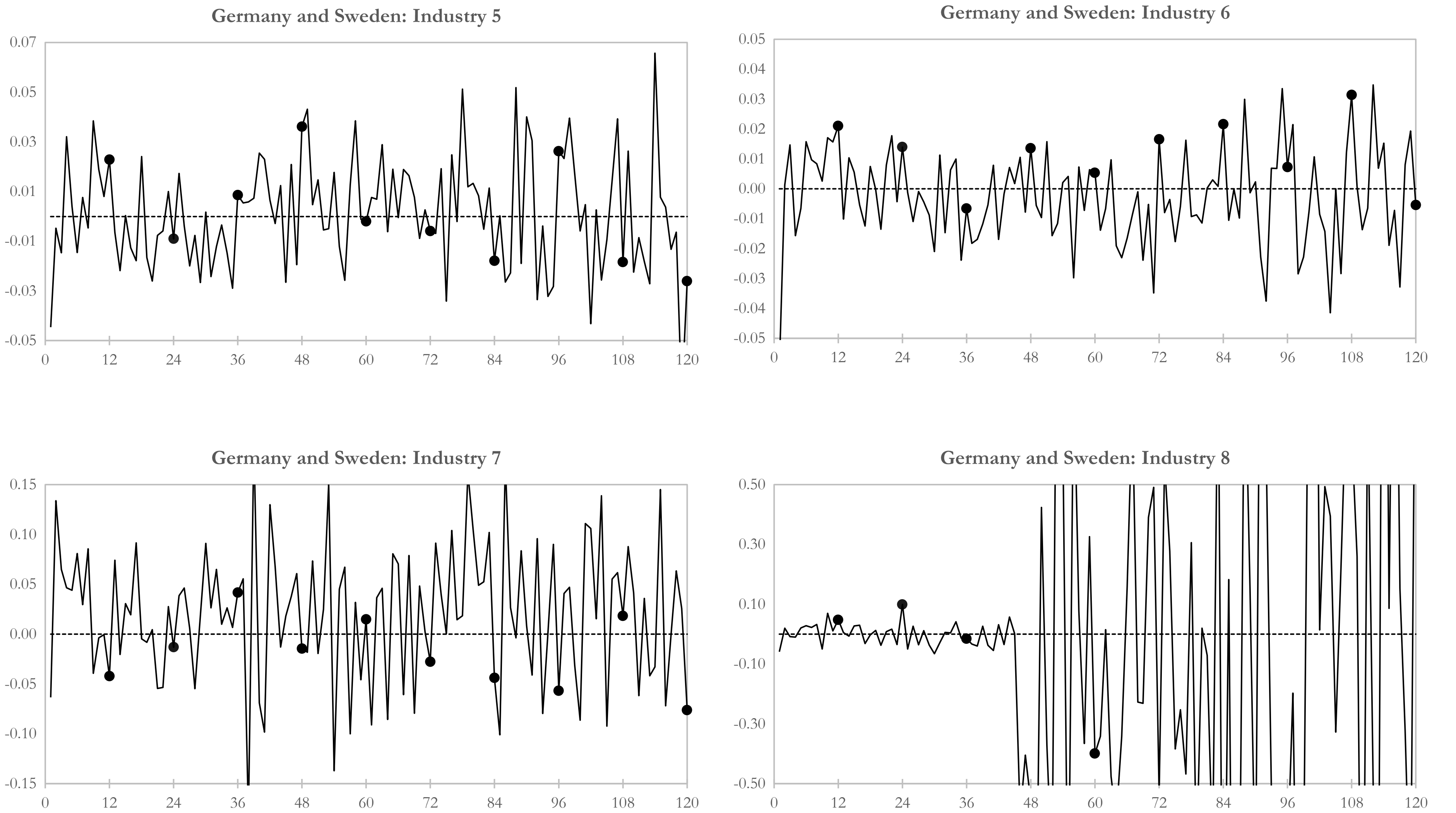


Figure VI: Industries 1 to 4 for Germany

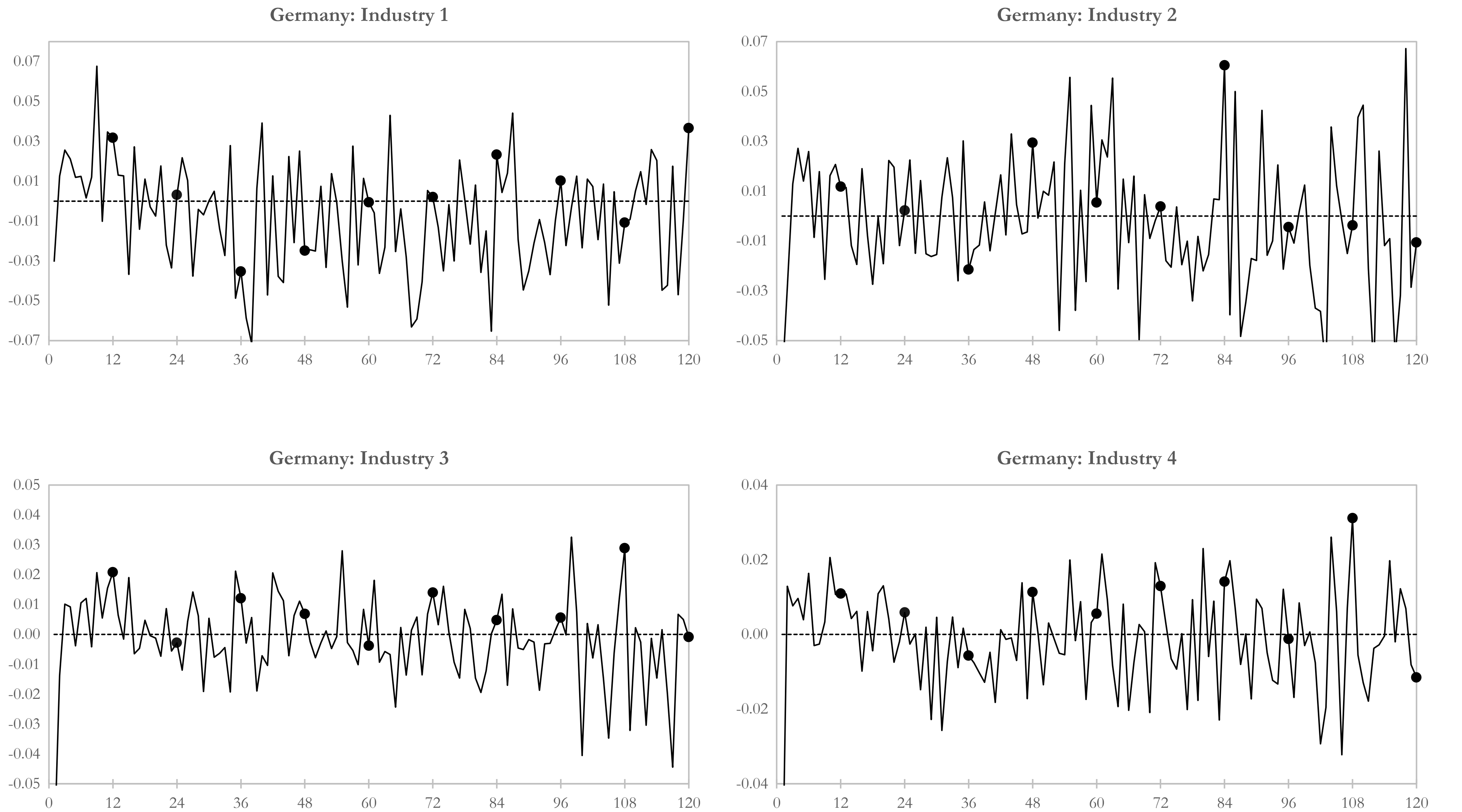


Figure VII: Industries 5 to 8 for Germany

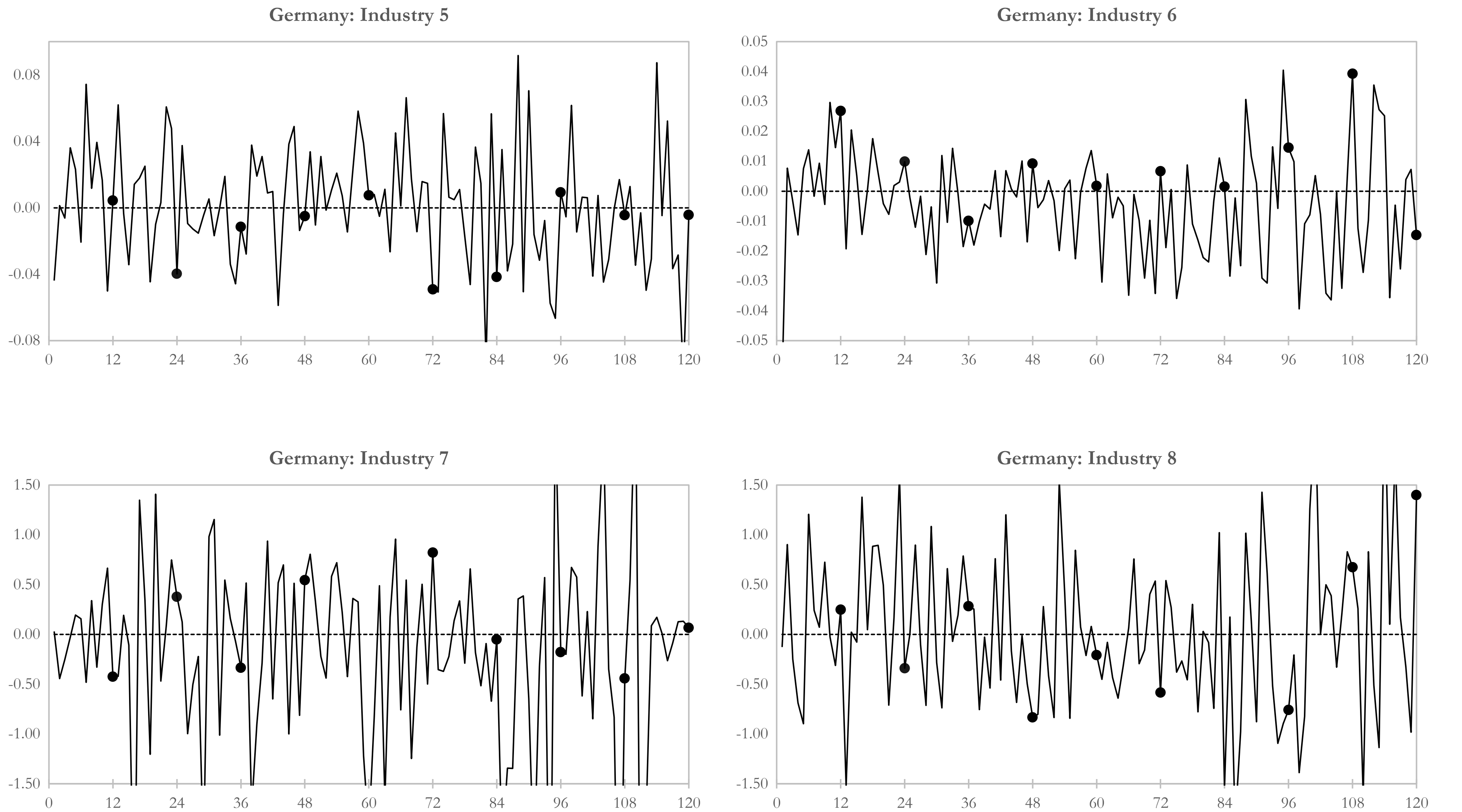


Figure VIII: Industries 1 to 4 for Sweden

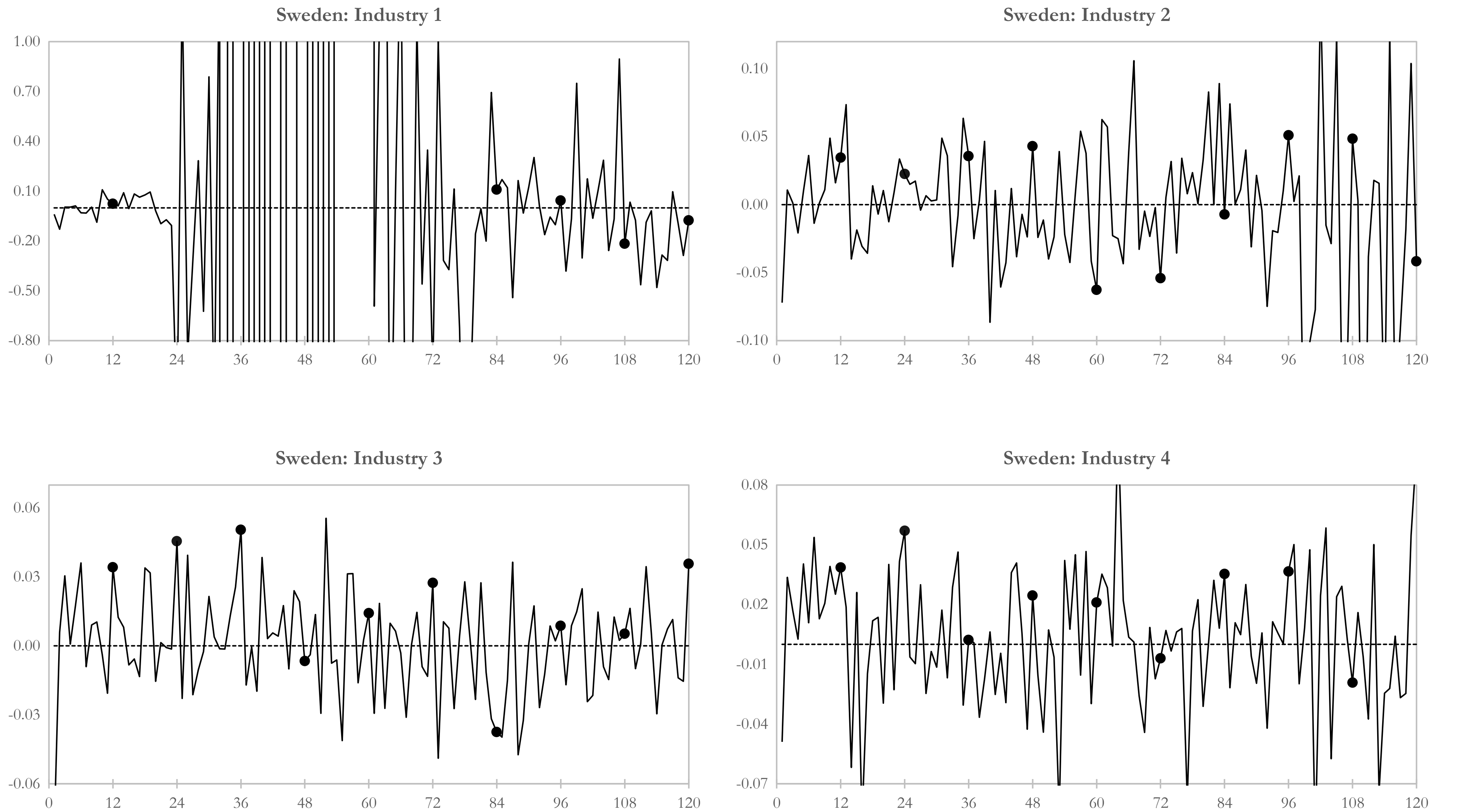


Figure IX: Industries 5 to 8 for Sweden