Master's Thesis

Reconciling Quality and Idiosyncratic Volatility Puzzles: A Study of the Effect of Stock Fundamentals on Pricing and Firm-Specific Risk

Abstract: The aim of the paper is twofold. First – to investigate the relation between quality of a stock, as measured by a set of its fundamentals, and its idiosyncratic return volatility. Second – to reconcile puzzling findings that idiosyncratic return volatility is priced with the fact that firm's quality (measured as a set of fundamentals using Asness, Frazzini and Pedersen (2013) methodology) is priced and hence to explore the pricing implications of the relation between the two. We find that in our sample of quarterly data on US listed firms since 1971 both higher quality and higher idiosyncratic volatility leads to positive premium. In addition, we document that idiosyncratic volatility and quality pricing work through different channels. Finally, we find that quality and idiosyncratic volatility are negatively related, however quality affects unpriced part of volatility only. This allows to conclude that by holding good quality stocks, investors are expected to earn a risk-adjusted premium and also hold less idiosyncratic risk.

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1 Introduction

Modern day finance research and practice fundamentally rely on the foundations laid down several decades ago. First, approach that lies in the heart of the modern portfolio theory, is due to Markowitz (1952). It revolutionized the concept of risk by providing mathematical framework for optimal portfolio construction – with capital markets in place people have to consider only statistical properties of the returns to make utility maximizing decisions. A decade later, using Markowitz' results, Sharpe (1964) and Lintner (1965) independently developed one the most influential models in Finance – the Capital Asset Pricing Model. It states that expected return on an asset is solely a function of expected market excess return. Consequently, the expected return is a function of *systematic* risk, and firm-specific (return) features should not be priced, i.e. *systematic* component of the variance of returns should be compensated, while *idiosyncratic* component should be diversified away in a well-constructed portfolio and hence there should be no compensation for loading on the idiosyncratic component.

Therefore, if the underlying assumptions of the two aforementioned models held in reality, there would be no concern for firm-specific or idiosyncratic risk. However, the evidence suggests that they do not hold. Consider the following: similarly to Markowitz' (1952) approach necessitating a *well-diversified* portfolio to eliminate idiosyncratic risk, CAPM assumes that it is optimal for all investors to hold a mix of *all* available risky assets in the proportion that they have in the market portfolio. In reality, this is regularly not the case; Blume, Crockett and Friend (1974, as cited in Levy, 1978) demonstrate that even in tax year 1971 investors held strongly concentrated portfolios: in the sample of over 17 thousand individual tax returns they find 34% individuals holding just one stock, 50% – not more than 2 stocks and only 10% – more than 10. Such patterns in individuals' portfolio composition persist decades later as well (Goetzmann & Kumar, 2008). Given such a vast exposure of investors to a firm-specific risk CAPM-defined world is unlikely to reflect reality and, as a result, idiosyncratic risk is a potentially major risk factor that could affect asset pricing and portfolio allocation decisions. We indeed see numerous studies (e.g. Goyal and Santa-Clara, 2003, or Ang et al. 2006) which find that firm-specific volatility and returns are related.

Furthermore, evidence exists on the relationship between returns and corporate announcements of fundamental news. For instance, Roll (1988) examines the effects of corporate events on stock returns immediately after the event take place and finds a very low R^2 which suggests that (announcements of) fundamentals are not immediately priced-in. A recent paper by Asness, Frazzini and Pedersen (2013) finds that quality of a stock (constructed as a collection of fundamental measurements) is a priced feature, with higher-quality (better fundamentals) stocks earning a sizable premium that is not accounted for by conventional pricing models.

Therefore, there are two separate lines of literature – one on pricing of idiosyncratic return volatility and another on pricing of stock quality – that present challenging findings which are difficult to reconcile with traditional asset pricing models. The relation between the two is typically reconciled using behavioural patterns of investors. Wei and Zhang (2001) suggest any irrational behaviour in the markets – bubbles, fashions, fads – is generally a consequence of information contained in the fundamental variables. There are behavioural explanations not only on investor side but on the corporate side as well. For instance, Jiang, Xu and Yao (2009) suggest that firms choose to disclose more (less) fundamental information if the earnings prospects are good (bad); as a result such vague disclosures enhance divergence of consensus among investors thus inducing additional idiosyncratic volatility in the stock returns. One of the main implications of additional idiosyncratic risk are extra costs for arbitrageurs. It turns out that these costs leave high idiosyncratic risk stocks more prone to under/over-reactions and this phenomenon introduces a positive or negative volatility-return relationship (Stambaugh, Yu & Yuan, 2013). This creates a potential channel for quality of stocks to be priced as well – if good quality reduces stocks' idiosyncratic volatility (i.e. via lower divergence of consensus on fundamentals), it would diminish behavioural inefficiencies, which would create quality-return effects offsetting volatility-return relationship. Another explanation is outlined by Campbell et al (2001) who argue that competition negatively affects fundamentals and quality, i.e. a more competitive environment puts pressure on profitability, capital structure, access to markets, etc. – fundamental measures that make up the overall quality of a firm. As a result, when success of one firm comes at the expense of the other – competition reduces correlation of their returns with the market and thus induces idiosyncratic volatility.

Regardless of the exact mechanism between quality and idiosyncratic return volatility the goal of this paper is twofold. First, we explore whether the two puzzling findings are actually one, i.e. **whether quality is priced-in through idiosyncratic return volatility channel**. Secondly, regardless of the pricing channel we investigate the relation between the two, namely we want to **establish fundamental factors that drive firm-specific risk**, as this would provide additional information that could be incorporated into portfolio construction process so that to optimize exposure to priced idiosyncratic volatility.

First, we find that both quality and idiosyncratic volatility are priced positively. The pricing of former is in line with Asness, Frazzini and Pedersen (2013) substantiating the behavioural under-reaction argument; and pricing of latter is in line with the implications of

Merton (1987) as well as Malkiel and Xu (2002). Unlike our initial expectation, we recognize that the most of pricing effects come from different channels thus refuting our prior that quality is the driver behind idiosyncratic volatility's pricing. Secondly, we document an elaborate study of predictability of idiosyncratic volatility by quality; generally we confirm the initial expectations and show that aggregate *profitability, growth, safety* and *payout* indices (components of quality measure proposed by Asness, Frazzini and Pedersen (2013)) are negatively related to firm-specific risk, although explanatory power of individual fundamental measurements is higher than that of aggregate quality scores. Estimated relations are also economically meaningful – a one standard deviation increase in quality measurement reduces idiosyncratic volatility by 29.5% of the cross-sectional and time-series average.

The rest of the paper is structured as follows. Section 2 outlines prior research on the behaviour and pricing on idiosyncratic return volatility. Section 3 presents the novel quality measurement that combines numerous fundamentals into one variable. Section 4 reconciles existing evidence on the relation between quality and idiosyncratic return volatility. Quality score construction as well as general description of the methods are presented in Section 5. Section 6 describes our findings and Section 7 discusses their implications; Section 8 concludes.

2 Idiosyncratic Volatility – Why Does It Matter?

A seminal paper by Campbell et al. (2001) provides overwhelming evidence on growing importance of idiosyncratic risk in the markets. In their paper, Campbell et al. (2001) employ daily stock returns in the sample period from 1962 to 1997 to calculate realized volatility and decompose it into three components – market-, industry- and firm-specific volatility. They find that during the sample period market and industry volatilities remained around their initial levels, while firm-specific volatility had a positive deterministic trend. The authors argue that this pattern has a broad implication for portfolio construction. Firstly, with idiosyncratic risk rising, R^2 of the market model decreases or, equivalently, correlation between stocks becomes smaller. Although, this creates stronger diversification benefits and, according to some studies, could mean more efficient pricing (e.g. Durnev et al, 2003), the authors show that the increase in idiosyncratic risk (which accounts for the most of the total risk) in '90s and early '00s, makes it necessary to hold more stocks to have a well-diversified portfolio.

Although the time trend proposition by Campbell et al (2001) is convincingly disputed by showing that the trend is driven by sub-period in the sample, the aggregate idiosyncratic volatility is still considered to follow a long memory process (e.g. Bekaert, Hodrick & Zhang, 2010, or Vozlyublennaia, 2011). Potential explanations for such behaviour are mostly related to the firms' fundamentals and are considered is Section 4 which ties together firm-specific risk and quality.

Another novel idea that market idiosyncratic risk could be determined by underlying factor(s) is presented in a recent paper by Kelly, Lustig and Nieuwerburgh (2012). The authors take individual stock returns and use Fama-French 3-Factor model (Fama & French, 1993, henceforth – FF3F) and principal components to obtain residuals that they use to construct realized firm-specific volatility measures. The authors find that while the factor models remove correlations among returns, they leave significant correlations among idiosyncratic volatilities of the stocks. The authors provide evidence that the correlation among idiosyncratic volatilities of stocks are robust even after sorting stocks into portfolios by industries and magnitude of volatility (i.e. the lowest pairwise correlation obtained by industry sorted portfolios is 67%). Furthermore, the authors argue that idiosyncratic volatility is by far the main driver of firms' total volatility. Finally, they try to test several simple one-factor models. They specify a volatility factor as equally weighted volatility of individual returns (they test total, FF3F and principal component volatility factors). In all three cases they find that around 36% of variation in cross sectional volatility can be explained with a simple factor model.

2.1 Theoretical Relation Between Firm-Specific Risk and Return

It is apparent that the magnitude and evidence on the structural behaviour of idiosyncratic volatility makes it important to research whether idiosyncratic risk could be an asset pricing factor. Theoretical considerations on this issue, however, are mixed and there is a number of papers that try to establish potential existence of idiosyncratic risk pricing channels.

One of the first attempts to explore a potential idiosyncratic risk pricing channel is due to Merton (1974) who suggests that equity could be seen as a call option on company's assets. In this light a permanent (unexpected) increase in the volatility of equity would signal an increase in assets' value variability, which by option pricing theory would mean that the value of the call option should rise, which implies that higher specific volatility should lead to higher returns. Another positive idiosyncratic risk pricing effect is suggested by the same author, but from a different perspective. The author states that due to information asymmetry, people tend to hold a limited subset of assets that they are best aware of. This leaves them under-diversified, and this way, from an investors' perspective, some of idiosyncratic risk becomes systematic and therefore could be rewarded (Merton, 1987). The validity of under-diversification assumption is somewhat supported by the recent evidence on individual's portfolio composition, which convincingly shows that under-diversification is an issue for most of individual portfolios (Goetzmann & Kumar, 2008). Another under-diversification argument version is presented by Malkiel and Xu (2002) who argue that the effective supply of the instruments that investors choose from is smaller than full available one. Since investors are constrained to obtain a market portfolio, this makes some of the idiosyncratic risk in the market impossible to eliminate, which by definition constitutes a systematic risk.

Although most of theoretical papers that consider idiosyncratic risk pricing postulate a positive idiosyncratic risk premium, there is some debate on negative pricing of such risk as well. One of the most cited arguments comes from a paper by Shlifer and Vishny (1997) that argues that short selling constraints make it difficult for arbitrageurs to drive security prices to efficient level. Since stocks with high idiosyncratic risk are more susceptible to producing higher (unjustified) positive returns, it takes time for arbitrageurs to drive their prices down to efficient level thus introducing a negative temporal pattern; this in turn implies a negative price of idiosyncratic return volatility. More recent evidence on this particular channel shows that generally, idiosyncratic volatility increases arbitrage risk. As a result stocks with higher idiosyncratic volatility will be susceptible to larger under/over-pricings, thus introducing positive/negative patterns in the stock returns. However, due to the fact that short-selling is asymmetrically less favourable than buying, on the aggregate scale overpricing (and negative patterns related to them), tend to dominate, thus appearing as a negative volatility – return relationship (Stambaugh, Yu & Yuan, 2013).

2.2 Empirical Evidence on Idiosyncratic Risk Pricing

Similar to theoretical motivation, empirical results on idiosyncratic risk pricing are also mixed. The beginning of the recent empirical debate on the positive pricing of idiosyncratic risk can be traced back to Goyal and Santa-Clara (2003) (henceforth – GS). The paper looks into idiosyncratic risk and finds that, while market lagged volatility does not have any predictive power over future market returns, equally weighted volatility of stocks in the market positively relates to future value-weighted portfolio returns. These finding are questioned by a number of papers. Wei and Zhang (2005), for example, extend the GS sample and replicate the study by looking at different subsamples. They find that positive predictability by GS is driven by the period in the '90s, and if this subsample is taken out the results become insignificant. Further support of the positive pricing of idiosyncratic risk comes from Chua, Goh and Zhang (2006). The authors acknowledge ambiguity in idiosyncratic risk pricing literature and suggest that it might be due to the fact that realized returns are poor proxies for expected returns, since on shorter horizons unexpected returns introduce a lot of noise. To investigate the problem the paper uses untraditional approach – decomposition of idiosyncratic volatility into expected and unexpected components. To do so they fit an autoregressive process on volatility based on FF3F residuals. The autoregressive part is then taken to obtain expected idiosyncratic volatility, whereas the error term becomes the unexpected part. The authors then prove that while coefficients on the relationship between expected volatility and realized returns are insignificant, including both volatility measures changes that and both become positively related to returns. The explanation the authors offer is that expected volatility positively relates to expected returns via Merton (1987) under-diversification argument, while there is also positive relation between unexpected returns and unexpected volatility, which could be seen as confirmation of optionality features of equity (Merton, 1974).

Overall, there is a rich body of literature that provides evidence on positive pricing of idiosyncratic risk. However, there is also a number of papers that suggest the opposite relation. One of the most controversial of them is due to Ang, Hodrick, Xing and Zhang (2006, henceforth – AHXZ). The authors compare returns on idiosyncratic-risk (obtained from FF3F) sorted portfolios and find that the stocks with high specific risk earn negative returns. They try to see if the phenomenon could be related to the aggregate volatility premium, however, they do not find strong evidence in support of the hypothesis, thus leaving it as a "puzzle". In their further work AHXZ extend analysis of this "puzzle" to international sample of 23 developed countries (Ang et al, 2009) and find that the findings remain strong outside of the U.S. markets – the average difference between the stocks in the highest and the lowest idiosyncratic risk quintiles is -1.31% on the monthly horizon.

An attempt to make a meaning of the "puzzle" was made by Jiang, Xu and Yao (2009) who suggest that corporations disclose more/less information depending on their prospect of earnings being good/bad. Authors argue that the vague disclosures (which are likely to be related with poorer future earnings) create a difference of opinion among the investors, thus introducing additional idiosyncratic volatility. Further, the authors suggest that due to the lack of sophistication of a marginal investor, this information content of volatility is not incorporated into prices contemporaneously but rather extends into time-series introducing the anomaly.

Similarly as with the papers finding positive firm-specific risk and return relationship, this line of literature is also met with some degree scepticism. One paper argues that AHXZ (2006) use a wrong proxy for volatility, as it is time-varying (Fu, 2009). Bali and Cakici (2008) try to look broadly at the mixed evidence on idiosyncratic risk and cross-sectional returns; they argue that the puzzle in AHXZ (2006) is driven by high concentration of illiquid and small stocks in the highest idiosyncratic risk quintile; the paper concludes by stating that no robust relation between the idiosyncratic risk and return exists.

In response to competing evidence on the pricing of idiosyncratic risk, a recent study tries to resolve the conflicts (Xu & Cao, 2010). The paper acknowledges potential pricing transition mechanisms raised by theoretical papers and argues that opposite sign effects often cancel each other out, thus resulting into conflicting or inconclusive evidence. It postulates that positive premium effects, due to under-diversified investors, are related to long run volatility, whereas limits to arbitrage argument (and negative premium) is more related to short term risks. After replicating the findings of the main papers it discusses that results are dependent purely on the selection of volatility measure, as some of them gauge long run volatility, while others are short term risk focused. The authors then are able to decompose firm specific risk into a short- and long-term components to find that, as the theory predicts, long-term component is priced positively, while short-term volatility component predicts negative returns.

Overall, in this section we show importance of the idiosyncratic risk, as well as present existing evidence on the pricing of thereof. In the following sections we attempt to relate it to stock quality through its fundamentals.

3 Fundamentals, Quality and Firm-Specific Risk

Abundant evidence exists on irrational behaviour of the prices on the market. It implies that on certain basis stock prices are subject to errors that are not always random. Wei and Zhang (2006) state that they often take the form of under-reaction or over-reaction to the information contained by the fundamental variables. Thus understanding the effect of fundamentals is crucial for understanding recent findings on idiosyncratic volatility. Therefore, in this section we consider the theoretical connection between idiosyncratic return volatility and fundamentals, as we as investigate the connection between the two.

3.1 Theoretical Link Between Fundamentals and Volatility

Irvine and Pontiff (2009) build a model to relate idiosyncratic return volatility and stock fundamentals. They start by arguing that in rational markets, prices must be equal to the present value of expected future cash flows to investors:

$$P_0 = \sum_{i=1}^{\infty} \frac{E_0(CF_i)}{(1+d)^i}$$

Therefore, changes in idiosyncratic volatility can be due to three factors:

1. Individual discount factor shocks provoke idiosyncratic volatility;
2. Cash-flow streams become more volatile;
3. Market is inefficient.

First, without having the means to prove or reject the latter explanation, there are only two possibilities left. Second, discount factor explanation is not convincing on theoretical grounds, as mainstream pricing models show that no premium should appear as a result of discount rate expectations change, as only the systematic component of the risk must be priced.

Therefore, the only remaining plausible explanation is variation in underlying cash flows. Irvine & Pontiff (2009) proceed by building a simple model illustrating the relation.

Assuming that $E_0(CF_i)$ in the equation above follows a random walk implies:

$$E_0(CF_i) = CF_0, \forall i \geq 0,$$

which simplifies it to:

$$P_0 = \frac{CF_0}{d}$$

By analogy:

$$P_1 = \frac{CF_1}{d} = \frac{CF_0 + \epsilon_1}{d}$$

where ϵ_1 is a random cash-flow shock at time *t=1*. In this setting realized return at *t=1* is then:

$$r_1 = \frac{P_1 - P_0}{P_0} = \frac{\epsilon_1}{dP_0}$$

and its variance is:

$$Var(r_1) = \frac{Var(\epsilon_1)}{dP_0}$$

Given that d and P_0 are determined at time *t=0*, they cannot contribute to the variation of return, and, hence all variance is due to variance of *unexpected cash flows*.

The model outlined above is defined on cash flows. However, there are much more measures of firms' fundamental performance which might be driving idiosyncratic risk or, for that matter, be the reason for its pricing. Therefore, we introduce a more comprehensive *quality* measure developed by Asness, Frazzini and Pedersen (2013, henceforth – AFP) and aggregate a number of fundamental measurements into a stand-alone quality score[3].

3.2 Quality Quantification

To our knowledge AFP's *quality score* is one of the first comprehensive attempts to formalize an exhaustive stand-alone measure of quality. It is based on fundamentals via the Gordon model:

$$\frac{P}{B} = \frac{1}{B} * \frac{Dividend}{Required\ Return - growth} = \frac{1}{B} * \frac{Profitabilty * PayoutRatio}{Required\ Return - growth}$$

where B, book value of equity, is introduced for scaling purposes. As a result, price is a function of *profitability*, *payout*, *safety* and *growth*. Assuming that quality is the characteristic investors are willing to pay for, higher quality assets should command higher price levels and thus have:

- Higher profitability (measured by margins, earnings and cash flows);

[3] Measures used in the AFP *quality score* can be tied to cash flows using accounting manipulations, thereby allowing the Campbell et al (2001) model to serve as a theoretical basis for the quality score relation to idiosyncratic return volatility.

- Higher growth (measured as changes in the profitability measurements);
- Higher payout (measured as debt/equity repurchases and proxies for returned capital);
- Higher safety (measured as market beta, leverage, credit quality and riskiness of earnings).

Indeed, APF find evidence that those characteristics imply higher valuation (in terms of Price-to-Book ratios) on the long sample of US stocks (1956-2012) and the broad sample of 24 developed markets (1986-2012); in both samples they show a significant positive relation between valuation (and hence price levels) and quality, which in turn substantiates the rationale for the quality score construction.

As a result, we have a comprehensive quality measure that is built on numerous measurements of firms' fundamentals. Hence, in line with Wei and Zhang (2006) proposition that frequently irrational pricing (i.e. return that is not captured by a pricing model – firm-specific return that results into idiosyncratic volatility) is a result of under-reaction to changes in the firm's fundamentals, the *quality score* can be used to investigate whether fundamental characteristics of the firm have any effect on the idiosyncratic return volatility.

4 Traces of Quality in Literature on Idiosyncratic Volatility Determinants

This section intends to explore in detail few established fundamental determinants of idiosyncratic volatility that are accounted for by the *quality score.* In addition, it appears that the evidence is unsystematic and only to limited extent successful in explaining the whole idiosyncratic volatility puzzle. Hence, the *quality* score might in fact turn out to be a unifying factor for the effect of different fundamentals. Next, we consider the evidence of fundamentals' effect on firm-specific risk clustered along 4 quality dimensions: *profitability, growth, safety & payout.*

4.1 Profitability and Earnings

Irvine and Pontiff (2009) employ a model presented in Section 3.1 to show the connection between idiosyncratic return volatility and volatility of earnings (measured by cash flows, earnings and sales per share). They perform the investigation on the aggregate market level and construct idiosyncratic volatility as equal-weighted squared difference between market and asset returns[4]. Volatility of cash flows is calculated as the residual from an autoregressive process fitted on explanatory variables on interest. The authors find a positively-sloping time trend both in aggregate average idiosyncratic volatility and in volatility of earnings (the trend is particularly persistent for cash flows and earnings per share). They report that while the annual increase in idiosyncratic volatility is ca. 6%, volatility of earnings reaches 16%. Therefore, the evidence

[4] Campbell et al (2001) show that the measure produces estimates of idiosyncratic volatility that very are similar to the market or FF3F model.

seems to prove Wei and Zhang (2006) proposition of under-reaction to fundamental news, in this case measured by earnings. However, as discussed earlier, later studies have shown that no trend exists in idiosyncratic return volatility, and that occasional findings of thereof are mostly due to specific sample periods; therefore while the paper leaves no doubts as to positive relation between firm-specific risk and volatility of earnings, the "trended" relation is, however, doubtful.

The Wei and Zhang (2006) proposition is further illustrated by Jiang, Xu and Yao (2009) who show that once controlling for future unexpected earning shocks idiosyncratic return volatility loses its predictive power over future returns, further substantiating under-reaction hypothesis. Wei and Zhang (2006) also focus on earnings (scaled by book equity, resulting into Return-on-Equity, ROE, measurement) and show in a cross-sectional setting that idiosyncratic return volatility is negatively associated with ROE, indicating that more profitable firms tend to have lower firm-specific risk.

Rajgopal and Venkatachalam (2008) are the only ones to our knowledge to focus on the relationship between quality and firm specific risk. They restrict the quality measurement only to quality of earnings. They construct two proxies for it, both based on accruals, (e.g. see Dechow and Dichev (2002) for construction) and in a cross-sectional setting document a negative relation between earnings quality and idiosyncratic return volatility, as measured using Campbell et al (2001) methodology. They rationalize it as follows: Easly and O'Hara (2004) and O'Hara (2003) postulate that the way a firm treats and recognizes its earning in the financial statement affects its information environment which translates into idiosyncratic volatility. The authors propose several potential economic mechanisms through which quality makes its way into return volatility. Firstly, firm-specific risk can increase because firms start to provide less detailed information in the statements. Secondly, it might be stimulated by more intensive trading by less sophisticated investors on the markets where spreading of different information is facilitated by advancement of information technologies.

Irvine and Pontiff (2009) explore another channel for quality to affect firm-specific volatility. They develop an analytical model showing that competition can induce idiosyncratic return volatility. They argue that when a consumer shifts from one firm to another, the first one loses earnings to the second, thereby implying lower correlation between them. They also show that competition among firms has been recently growing in the US economy, as a result the correlation between the firms, and between the firms and the market has being declining resulting into higher idiosyncratic return volatility. In their study Irvine and Pontiff (2009) employ several proxies for competition among which is return-on-assets (ROA). They find evidence that firms with higher market power (lower competition) have higher expected returns but also lower idiosyncratic risk. This means that through lower competition higher profitability (equivalently – higher quality) leads to lower firm-specific risk. Comin and Philippon (2005) employ a different approach to present similar findings: they show that turnover among leaders in the industry (i.e. competition) affects idiosyncratic return volatility. Also they show that profit margins are a proxy not the driver of the effect, as they remain the same *conditional* on the firm remaining the leader in the industry; hence being a leader (i.e. facing lower competition) is what drives idiosyncratic volatility, not the level of margins.

Overall, existing evidence allows to postulate that *profitability* dimension of the *quality score* should be negatively related to the idiosyncratic return volatility.

4.2 Growth

Fink et al (2004) relate idiosyncratic return volatility to firm age and listing requirements. They show that there has been an increase in the number of new listing in 90's - early 00' accompanied with the decline of average firm age at IPO (from ca. 40 years in 60's to less than 5 years in 90's) which is driving the increase in the idiosyncratic return volatility during the period. The authors rationalize the finding as follows: equity of younger firms generally represents claims on the cash flows that occur further in future, as a result of which there is more uncertainty and more firm-specific risk. Brown and Kapadia (2007) arrive at similar conclusions and go further to show that there is a decline in quality of firms that make IPOs. Their finding is that idiosyncratic risk of firms who list at younger age does not decline with age, implying that riskier young firms tend to stay such. Wei and Zhang (2006) in turn argue that the age effect is due to younger firms having higher earnings volatility which drive the idiosyncratic risk.

Therefore, we expect *growth* dimension of quality measure to be positively related to idiosyncratic return volatility.

4.3 Safety

Wei and Zhang (2006) construct Variance of ROE measurement (VROE) as the standard deviation of ROEs over the preceding 3 years and show in the cross-sectional setting that idiosyncratic return volatility is positively related to VROE, implying that lower safety of a stock leads to higher firms-specific risk. In addition they estimate equitation where both ROE and VROE are considered as explanatory variable for idiosyncratic return volatility and find that both remain significant and retain their signs, providing initial evidence that different dimensions of quality explain different variation in firm-specific risk.

All in all, higher *safety* should also be associated with lower firm-specific risk.

4.4 Payout

To the best of our knowledge, no formal investigation into the relation between *payout* and idiosyncratic return volatility exists. However, Jensen (1986) builds a theoretical argument stating that higher cash balances in a firm induce managerial conflicts of interest streaming from management having less incentives to use existing resources efficiently. Therefore, firms that return more cash to shareholders should make better investment decisions that enhance shareholder value while making the firm safer and inducing higher quality. If investors underreact to fundamentals, then safer firms (higher quality) should have lower firm-specific risk. Thus, we expect a negative relation between *payout* and idiosyncratic return volatility.

4.5 Formulation of Hypotheses

The systematic under-reaction to firms' fundamentals ties together idiosyncratic return volatility and quality. As explained in Section 2 firm-specific volatility, on contrary to conventional models, is arguably a priced feature. Therefore, by extension it is reasonable to expect that quality through fundamentals could be priced as well. And indeed by sorting stocks into 10 portfolios based on the quality measure AFP show this by documenting a strong pattern in alphas: they are monotonously increasing from -0.53 (-0.67) for CAPM (FF3F) to 0.18 (0.29) when changing from lowest to highest quality portfolios. Thus, both idiosyncratic return volatility and quality could be interconnected due to under-reaction proposition. As a result, it is natural to expect that quality might in fact be driving idiosyncratic volatility which in turn affects the returns:

H1: Quality of a stock drives the idiosyncratic return volatility which in turn affects returns.

If the quality is priced through idiosyncratic volatility, then the relation between the two calls for a separate investigation as well. In this section we presented existing evidence on how most individual components of 3 out of 4 dimensions of quality (except *growth*) are expected to be negatively related to the firm-specific risk. Thus, we expect the negative effect to dominate which allows to extend the existing evidence to hypothesize that:

H2: Idiosyncratic return volatility is a negative function of quality.

Therefore, if we find that indeed quality is negatively related to idiosyncratic return volatility, then the only case when quality can be priced-in through idiosyncratic return volatility channel is when a) quality has a positive effect on returns and idiosyncratic volatility has a negative; or b) quality has negative and volatility – positive. Existing literature favours the first option, as it has been documented that quality is positively priced and volatility in some settings – negatively (i.e. Ang et al, 2006). In this case, if we document a negative relation between quality and idiosyncratic return volatility, and at the same time any different combination of pricing effects than the two described above (i.e. that quality and firm-specific volatility would not affect returns in the opposite directions), this would also provide the basis for rejection of *Hypothesis 1*.

5 Methodology

This section considers the methods employed to test formulated hypotheses. Firstly, we describe the data used; secondly we consider construction of the quality and firm-specific risk proxies. Lastly, we present methods used to explore the pricing channel between idiosyncratic volatility and quality as well as to quantify the relationship between them.

5.1 Data

The sample is meant to cover the whole universe of US listed common stocks, however, it is restricted by data availability. The primary data source is CRSP/Compustat merged database. Compustat is used to obtain quarterly accounting data needed for quality score construction; for majority of variables quarterly tapes start in 1971, and run till 2013, resulting into 169 quarters, or 42.25 years of data. CRSP is used as a primary source for daily stock prices, Fama-French (1993) and Carhart's (1997) factors as well as the risk-free rate We focus only on common stocks[5] that are listed on the major exchanges – NYSE, NASDAQ and AMEX. The initial screening of CRSP database results into 23,621 firms with CRSP/Compustat merged database having accounting variables for all of them. We further restrict the sample to firms listed for more than 20 quarters (as calculation of certain variables require at least 5 years of data). This results into final sample of 11,792 firms, corresponding to 667,080 firm-year observations. The data is winsorised at 2% level, i.e. 1% on each end of the distribution.

All accounting variables are in millions USD; stock returns and factors are in USD as well. To address the non-synchronicity in data, namely that firms have fiscal quarters not necessarily corresponding to calendar ones, we use Copmustat's variable DATACQRT to determine the calendar quarter during which a firm's quarter ends. The variable is constructed as follows: it assigns fiscal quarters that end in February, March and April to calendar quarter 1, and similarly for the remaining quarters. As US firms have at most 45 days to file the quarterly report (SEC, 2012), all of the firms that reported in the aforementioned month will report the results by the end of the second calendar quarter. Hence, we use the DATACQTR variable to assign all fiscal quarters to calendar quarters and match them with the measure of firm-specific risk (constructed separately from daily prices) for the following calendar quarter to insure that the accounting data has been reported and has reached the market and as a result got incorporated into the prices.

[5] We use the following CRSP share class codes (SHRCD) to pick common stocks only: 10, 11 and 12.

5.2 Quality Score Construction

In constructing the quality score we tightly follow AFP approach, as it provides an innovative way to combine various fundamental measurements, but extend it to quarterly data. The measures are clustered along four quality dimensions – *profitability*, *growth safety* and *payout*. The quality measurements are constructed as follows (see Appendix A).

Profitability is broadly defined as a set of different margins: gross profit over assets (GPOA), return on equity (ROE), return on assets (ROA), cash flow over assets (CFOA), gross margin (GMAR) and portion of the accounting net earnings that are actually cash earnings (i.e. low accruals, ACC).

To put all the profitability measurements into an aggregate *profitability* score we standardize each individual measurement to calculate the z-score:

$$z_{j,i,t} = \frac{x_{j,i,t} - \bar{x}_{j,t}}{\sigma_{j,t}}$$

where $x_{j,i,t}$ ($z_{j,i,t}$) is the (standardized) profitability measure j for firm i in period t, $\bar{x}_{j,t}$ and $\sigma_{j,t}$ are the cross-sectional mean and standard deviation of profitability measure j in period t, respectively.[6] To arrive at the aggregate *profitability* score we take an average of z-scores for all profitability measurements for each time period:

$$z(profitability)_{i,t} = \frac{1}{6}\left(z_{GPOA,i,t} + z_{ROE,i,t} + z_{ROA,i,t} + z_{CFOA,i,t} + z_{GMAR,i,t} + z_{ACC,i,t}\right)$$

We construct *growth* dimension of quality score in a similar fashion. We define it as 5-year (20 quarters) growth in the profitability measurements – we relate the 5-year change in the numerator (profits or cash-flow) of the margins to the 5-year lagged value of the denominator; for instance, 5-year growth in return on assets is calculated as:

$$\Delta ROA = \frac{NI_{i,t} - NI_{i,t-20}}{AT_{i,t-20}},$$

where $NI_{i,t}$ and $NI_{i,t-20}$ is Net Income in the period t and 20 quarters ago, respectively, and $AT_{i,t-20}$ are 5-year lagged Total Assets.

The aggregate *growth* score is calculated as the cross-sectional average of individual standardized measurements:

$$z(growth)_{i,t} = \frac{1}{6}\left(z_{\Delta GPOA,i,t} + z_{\Delta ROE,i,t} + z_{\Delta ROA,i,t} + z_{\Delta CFOA,i,t} + z_{\Delta GMAR,i,t} + z_{\Delta ACC,i,t}\right),$$

where Δ indicates 5-year growth.

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[6] We standardize based on available information for all stocks in the sample, not just those that have observations on all (19) quality measurement, so that to use the full distribution of available outcomes and also in order not to introduce a "data availability" bias.

The *safety* dimension of quality is defined as companies having low market beta (BAB), low leverage (LEV) and low bankruptcy probability (O-Score, due to Ohlson (1980), and Z-Score, due to Altman (1986))[7]. The aggregate *safety* score is similarly an average of four standardized measurements:

$$z(safety)_{i,t} = \frac{1}{4}\left(z_{BAB,i,t} + z_{\mathrm{LEV},i,t} + z_{\mathrm{O-Score},i,t} + z_{\mathrm{Z-Score},i,t}\right)$$

Payout component of quality score is defined as net debt (DISS) and equity (EISS) issuance and total payout over profits (NPOP). To arrive at the aggregate payout score we standardize individual measurement and take the cross-sectional average of thereof:

$$z(payout)_{i,t} = \frac{1}{3}\left(z_{DISS,i,t} + z_{\mathrm{EISS},i,t} + z_{\mathrm{NPOP},i,t}\right)$$

Finally, we construct the aggregate *quality score* by averaging scores for four quality dimensions:

$$Quality\ Score_{i,t} = \frac{1}{4}\left(z_{profitability,i,t} + z_{\mathrm{growth},i,t} + z_{\mathrm{safety},i,t} + z_{\mathrm{payout},i,t}\right)$$

5.3 Idiosyncratic Return Volatility Measurement

As the most of the literature suggests we use Four-Factor model that includes three Fama French (1993) factors and Carhart's (1997) momentum factor as a benchmark to obtain our idiosyncratic returns. Thus, our returns equation becomes:

$$R_{i,t,\tau} - r_{f,t,\tau} = \alpha_{i,t} + \beta_{i,t}\left(R_{m,t,\tau} - r_{f,t,\tau}\right) + s_{i,t}SMB_{t,\tau} + h_{i,t}HML_{t,\tau} + u_{i,t}UMD_{t,\tau} + \varepsilon_{i,t,\tau},$$

where i is firm, t is a quarter in the sample and τ is a day within a quarter. This way for each stock within our period we obtain a series of independent idiosyncratic returns ($\varepsilon_{i,t,\tau}$) which we use to construct our realized volatility measure for each quarter:

$$IVOL_{i,t} = \frac{250}{\tau_{t,i}} \sum_{\tau=1}^{\tau_{t,i}} \varepsilon_{i,t,\tau}^2,$$

where $\tau_{t,i}$ reflects a total number of days for a company i at a quarter t.

There is ongoing evidence that the selection of the volatility measure can capture varying loading on different volatility components (Xu & Cao, 2010), however due to our frequency limitations to quarterly data, we cannot use rolling windows, while using a weighting scheme would produce volatility that is most reflective of the end of the quarter, which would also be a mismatch with our quality observations. As a result, we argue that simple realized volatility measure is the best given the data limitations at hand. In addition, by including Fama-French's

[7] We exclude low idiosyncratic volatility component from the safety dimension of quality measure proposed by AFP as it would artificially create strong co-relation between the quality and firm-specific risk.

and Carhart's factors we also eliminate the bias introduced by using simpler models, for instance, when using simple excess return over the market, size becomes a significant determinant of idiosyncratic volatility, which is a shortcoming of the model employed (that does not control for known asset-pricing features) rather than an actual relationship.

5.4 Returns Interaction with Quality and Volatility

We begin our econometric analysis by trying to find a relationship between returns and quality, while trying to see whether this relationship changes while controlling for idiosyncratic risk estimated using methodology outlined in the previous section. While there are several ways to research this question (the standard being a two-step procedure, where in the first step one obtains a cross-section of alphas and in the second step those alphas are regressed cross-sectionally on average values of independent variables), we choose a panel factor model, as it provides most comparable and comprehensive results due to using a single step procedure. We define our panel model as:

$$R_{i,t+1}^{e} = \left(\alpha + \alpha_q' Q_{i,t} + \alpha_{IVOL} IVOL_{i,t+1}\right) + \left(\beta + \beta_q' Q_{i,t} + \beta_{IVOL} IVOL_{i,t+1}\right)' F_{t+1} + \varepsilon_{i,t+1}$$

The left hand side variable here is a stock return for quarter $t + 1$ in excess of quarterly risk-free rate. On the right hand side we control for a 4 factor model (Fama and Fench (1993) 3 factors and Carhart's (1997) momentum factor) and to be extra diligent, we add interaction terms between factors and quality, to control for the possibility that quality can be related to the factors. α_q' then becomes a vector of interest that represent coefficients on quality (and its sub-scores). They allow us to see how quality measures affect alphas – risk adjusted performance of the stocks. By including idiosyncratic risk together with the quality measurements we can see how the coefficients change compared with a stand-alone case. Both idiosyncratic volatility and returns enter the equation as leading variables to address the fact that fundamentals needed for quality score construction in quarter t become available in the following period, i.e. in quarter $t + 1$.

Finally, we also rerun the model using constituents of quality components as independent variables. This way we can see, which of the measurements drive the results, as well as take a closer look at how the effects change when idiosyncratic volatility is included.

5.4.1 Pricing of Expected Volatility

After testing quality's effects on risk-adjusted performance, and its pricing interplay with idiosyncratic volatility via including it as a control, we want to see if quality is responsible at least for a part of priced volatility. To research the issue, we create expected volatility measure using information on stock's past quality by employing adjusted methodology described below.

In their paper, Chua, Goh and Zhang (2006) argue that idiosyncratic risk is priced, via two components – expected and unexpected volatility. As a result, they propose decomposing realized idiosyncratic volatility into expected and unexpected components and then regress them on returns to see the pricing effects. To do so, they assign autoregressive process to realized volatility and thus the residual becomes unexpected realized volatility:

$$IVOL_{i,t} = \alpha_i + \sum_{l=1}^{L} \rho_{i,l} IVOL_{i,t-l} + \epsilon_{i,t}$$

$$EIVOL_{i,t} = \alpha_i + \sum_{l=1}^{L} \rho_{i,l} IVOL_{i,t-l}$$

$$UIVOL_{i,t} = \epsilon_{i,t},$$

where $EIVOL_{i,t}$ is expected component of volatility and $UIVOL_{i,t}$ is residual noise (innovation) for stock i in quarter t.

In the spirit of the methodology they use, we include a third component that is – quality-based volatility. We include lagged quality measure values into our regression (we choose to use 1 lag only, as individual time-series often have a limited number of observations) and re-estimate following equations for each stock separately:

$$IVOL_{i,t} = \alpha_i + \rho_{i,1} IVOL_{i,t-1} + q_{i,1} Q_{i,t-1} + \epsilon_{i,t}$$

$$EIVOL_{i,t} = \alpha_i + \rho_{i,1} IVOL_{i,t-1}$$

$$QIVOL_{i,t} = q_{i,1} Q_{i,t-1}$$

$$UIVOL_{i,t} = \epsilon_{i,t}$$

Having obtained these measures for each stock i we are able to test the relation using them as independent variables in a panel regression setting:

$$\alpha_{i,t} = \phi_0 + \phi_1 EIVOL_{it} + \phi_2 QIVOL_{it} + \phi_3 UIVOL_{it} + \eta_{i,t}$$

where α_{it} is the constant (average risk-adjusted performance) from the four-factor model (Fama-French (1993) 3 factors and Carhart's (1997) momentum factor) for stock i in quarter t re-estimated using daily frequency for each quarter and then multiplied by 60 to reflect quarterly frequency. This approach, firstly, allows us to look for the evidence on whether some part of idiosyncratic risk pricing is coming from a fundamental quality channel. Secondly, it works as a robustness check for the previous part – we expect the changes in coefficients between volatility-controlled and uncontrolled regressions be reflected in these tests. Namely, if quality affects priced volatility component, the sign of quality-predicted volatility should be coherent with the coefficient changes in the previous part. Finally, the results obtained by this and the previous section, should make a ground for further volatility-quality investigation.

5.5 Investigating the Relation Between Quality and Volatility

Once the pricing channel between quality and idiosyncratic return volatility is established, we proceed with investigating the relation between the two further. For this purpose we estimate a series of regressions of the following form:

$$IVOL_{i,t+1} = \alpha + \sum_{p=1}^{P} q_p Q_{p,i,t} + \epsilon_{i,t+1}$$

Our dependent variable being realized idiosyncratic volatility, while independent variables are *quality score* and 4 of its dimensions; first, we consider them individually in a separate specification, and then pool 4 quality dimensions together. If we confirm the relation between them, then we disaggregate the dimensions into their components. Idiosyncratic return volatility enters the equation as a leading variable to address the fact that fundamentals needed for quality score construction in quarter t become available in the following period, i.e. in quarter $t+1$.

5.6 Model Consideration

We estimate all final models on firm-level, i.e. in a panel data setting. We begin with testing the panel for stationarity and proceed with data either in levels or changes, depending on the necessity to transform it. We employ the Im-Pesaran-Shin (Im, et al, 2003) panel stationarity test. The test is among a few designed to work with unbalanced panels and it also allows for varying autoregressive parameters across firms within a panel. Essentially, it performs the augmented Dickey-Fuller test for each entity in the panel, and tests if *the average* entity in the panel is stationary.

Secondly, to account for potential cross-sectional and autocorrelation in residuals and thus to produce more robust estimates, we opt for using standard errors clustered by two dimensions – time dimension and firm dimension:

$$\hat{V}[\hat{\beta}] = \hat{V}^{I}[\hat{\beta}] + \hat{V}^{T}[\hat{\beta}] - \hat{V}^{I\cap T}[\hat{\beta}],$$

where $\hat{V}^{I}[\hat{\beta}]$ is the variance-covariance matrix estimated along entity dimension, $\hat{V}^{T}[\hat{\beta}]$ - along time dimension, and $\hat{V}^{I\cap T}[\hat{\beta}]$ is the diagonal matrix at the intersection of matrices $\hat{V}^{I}[\hat{\beta}]$ and $\hat{V}^{T}[\hat{\beta}]$, as both of them have the same diagonal and thus double-counting has to be eliminated. With observations grouped into G clusters of N_g observations, for $g = \{1, 2, \dots, G\}$, variance-covariance matrix of standard errors clustered along one (time or firm) dimension is estimated as:

$$\hat{V}^{G}[\hat{\beta}] = (X'X)^{-1}\hat{B}(X'X)^{-1}, \qquad \hat{B} = \sum_{g=1}^{G} X'_g u_g u'_g X_g,$$

where X_g is the N_g x K matrix of regressors and u_g is the N_g x 1 vector of residuals for cluster g. Using procedure outlined above we estimate variance-covariance matrices clustered by firm and time, and by subtracting the diagonal variance-covariance matrix arrive at standard errors clustered by both dimensions. Petersen (2009) reports that unlike using fixed effects, double clustering allows for the specific effects to vary over time (e.g. firm effects to decay over time), which is expected to produce more consistent estimates of standard errors.

6 Empirical Findings

Table B1 (Appendix B) presents the cross-sectional and time-series descriptive statistics of the variables used in construction of the AFP *quality score*. The table shows that by relying on a wide dataset with long time series the sample includes very different firms. For instance, profitability varies greatly from highly lucrative firms that in some quarters report ROEs of up 60% to potential bankruptcy cases with ROEs falling below -100%. While extreme cases vary greatly, the average firm in an average quarter marginally loses money on the bottom-line (slightly negative ROE, ROA, etc.). The case extends to the level of risk of firms in the sample; for example, Frazzini and Pedersen (2013)'s market beta in in range between highly counter-cyclical -3.53 to highly risky 5.76, with the average level of risk slightly below the market of 0.9 (BAB is defined as negative of market beta calculated using Frazzini and Pedersen (2013) methodology). In terms of payout, an average firm in an average quarter is marginally issuing both debt and equity (2% and 6%, respectively)[8].

Data availability varies across variables, but for majority of them it is around 70%. However, the quarterly cash flow data is extremely poor and is available for barely 33% of firm-quarter observations (and falls to 13% when 5 year growth is calculated); therefore henceforth the cash flow over assets variable (CFOA) and well as its growth (ΔCFOA) are excluded from the analysis to utilize maximum of available data.

6.1 Preliminary Investigation of the Historical Quality – Idiosyncratic Volatility Relationship

To illustrate historical development of quality and firm-specific risk we aggregate individual sub-scores, total quality scores and idiosyncratic volatilities into average equally- and value-weighted aggregate indices[9].

[8] Both EISS and DISS are defined as the opposite of the net issuance, and, hence, represent repurchases.

[9] In order to control for non-synchronicity in reporting we use market capitalization in the consecutive quarter to calculate the weights; this allows to insure that all fundamental information is known to the market before we calculate the average quality score. Similarly, as discussed before, idiosyncratic volatility as also leading by 1 quarter. In order for a firm to be included in the aggregate volatility and quality (sub)score indices in a particular quarter, we require that it has observations on all quality measurements and idiosyncratic volatility. As a result, first 4 years of

Table B2 (Appendix B) presents descriptive statistics of the aggregate quality and idiosyncratic volatility indices. Several patterns emerge from comparison of average scores. Firstly, average quality sub-scores are higher when weighting scheme based on market capitalization is applied, which suggests that larger firms have better quality, or expected quality is a valued feature. Secondly, there is an exactly inverse relation for idiosyncratic volatility – it is lower on value-weighted basis, than on equally-weighted, indicating that larger firms on average have significantly lower idiosyncratic risks. Similarly, volatility of value-weighed aggregated idiosyncratic risk index is lower, suggesting that bigger firms' average specific risk is more stable over time and does not experience swings resulting from changes in sentiment or fundamentals. This generally goes in line with consensus that smaller firms tend to be riskier and hence, by construction, more volatile.

Figure C1 (Appendix C) presents the historical development of aggregate quality (sub)indices and idiosyncratic volatility since 1980 until 2012. The charts show that almost from the beginning of the period the equally-weighted volatility was on the rise until early 2000's; this period is in the focus of the pioneering studies on idiosyncratic volatility (e.g. Campbell et al, 2001) that generally document an increase (together with a time trend) in the idiosyncratic return volatility. The period has three sizable spikes – 1987, 1992 and 1999-2002. Two of the crisis – Black Monday in '87 and dot.com – are also reflected in value-weighted series, indicating that the crises were severe and across the board, while crisis in 1992 affected only small-cap stocks. However, since 2003 the equally-weighed idiosyncratic volatility index has been decreasing, with a significant spike in 2008-2009, corresponding to the financial crisis. Therefore, the longer time series that we employ suggest that an increase in idiosyncratic risk documented in earlier literature is largely a temporary issue. Comparison of equally- and value-weighted idiosyncratic volatility indices allows to conclude that changes in market-wide average firm-specific risk are mostly driven by smaller firms; in addition average idiosyncratic risk for larger firms appears to be lower than for smaller ones.

As for quality and its dimensions, first, average market-wide *profitability* has increased for larger firms, while declined for smaller ones. Also, the former was on the rise until middle of dot.com bubble, and remains flat since. Second, *growth* remained on the same levels for both equally- and value-weighted indices, except for a spike during the dot.com bubble. Interestingly, the financial crisis was associated with much smaller growth. Third, as expected, *safety* score is higher of larger firms and while it was on rather similar level with equally-weighted index in

the sample (1976-1979) have very poor data availability for all measures, and hence are excluded from the aggregate indices, as it is unreasonable to draw conclusions about market situation in a particular quarter based only on a few observations.

1982, since then the two have been diverging, indicating increasing safety of larger stocks. Fourth, *payout* appears rather independent of size and remains flat over the years with exception of dot.com bubble, when growing internet stocks returned very little money to shareholders and thus value-weighted *payout* strongly declined. Lastly, total *quality score* is also driven by larger firms and until dot.com was on the rise, while ever since it has remained rather flat.

We also formally investigate the characteristics of historical development of quality and volatility indices primarily in order to formally reject Campbell et al (2001) proposition of a time trend in the idiosyncratic return volatility. For this purpose we perform augmented Dickey Fuller tests, the results of which are provided in Table D1 (Appendix D). Stationarity analysis shows that in most of the cases equally-weighted series tend to reject non-stationarity against all three alternatives (being simple stationary process, stationary with a drift and time trend stationary), whereas in value-weighted series non-stationarity is mostly rejected only against stationary process with the drift alternative. Nevertheless, the ADF tests provide enough evidence to conclude that idiosyncratic volatility is a stationary process, hence confirming that Campbell et al (2001) findings are driven by subsample issues. In addition, quality index and sub-indices are mostly stationary, thereby indicating that there is no persistent deterioration or improvement of market-wide average quality.

From the analysis of historical development and properties of quality and volatility series we primarily conclude that both of them are stationary, thus rejecting the proposition of possible trending or co-trending. Graphical representation of average idiosyncratic volatility and quality also suggests that there are at least periods when the two develop rather similarly, which indicates that both, while having an effect on returns, might have it through the same channel. Namely, if idiosyncratic volatility is a result of under-reaction to firms' fundamentals, then the pricing of the former might actually be a consequence of the latter. Hence, further we investigate whether pricing of idiosyncratic volatility is to any extent driven by pricing of quality.

6.2 Idiosyncratic Return Volatility as a Pricing Channel for Quality

As described in Section 5.4 we conduct panel factors analysis to investigate whether pricing of idiosyncratic return volatility is merely a channel for pricing of quality[10]. So, first, we consider stationarity of the panel by employing Im-Pesaran-Shin (Im et al, 2003) panel stationarity test. Table E1 (Appendix E) presents the test results[11]. The results are strong and firmly allow to

[10] To be included in the sample, we require a stock to have idiosyncratic volatility and quality data for at least 20 consecutive quarters; this results into 2,302 stocks over 138 quarters and roughly 90,000 firm-quarter observations.

[11] To enhance the power of the test we include lagged value of the dependent variable, where number of lags is selected for each entity in the panel according to AIC with maximum 4 lags (to account for any possible seasonality

reject the hypothesis of all entities in the panel having a unit root; alternatively, the tests show that *an average* firm in the panel is stationary. Therefore, we proceed with estimating the relationship between quality and idiosyncratic return volatility in levels.

The panel factors analysis allows to relate both quality and idiosyncratic volatility to alphas. Also it enables to see if the results for two control each other out, thus obtaining evidence with the respect to *Hypothesis 1* – whether idiosyncratic volatility is merely a channel through which quality is priced. As stated in methodology, the technique presupposes regressing excess returns on independent variables, factors and interaction variables to control for a possibility that different levels of quality could interact differently with the factors (thus providing more flexibility). Since there is a substantial number of these controls (4 factors in each regression as well as 4 interactions per independent variable), Table 1 reports only main coefficients which present the impact of independent variables – quality and idiosyncratic return volatility – on risk-adjusted returns.

First of all, the results suggest that there is a significant relation between quality and returns. Specification IV shows that estimates on three out of four quality sub-scores are highly statistically significant and show a positive premium earned by higher-quality stocks. The aggregate score is dominated by *profitability* and *growth* dimensions, while we find *safety* not to be related to returns at all. The estimates in the table tend to agree with the findings of Asness, Frazzini and Pedersen (2013), as we also see that higher quality stocks tend to earn higher returns. Specification II reports the economically substantial effect of a stand-alone *quality score* – if it increases by one standard deviation (0.2745), realized risk-adjusted return increases by 2.15% on quarterly basis. This again supports AFP findings that good quality stocks are under-priced by employing a completely different estimation methodology

Also we find strong evidence that idiosyncratic return volatility matters for pricing – Specification I shows that a one standard deviation (.5208) increase in idiosyncratic volatility boosts return by 1.73% per quarter on risk-adjusted basis. Finally, looking at Specification III allows us see whether quality and idiosyncratic volatility measure the same thing. To find the evidence to our *Hypothesis 1*, we would expect quality to control out all of the volatility effects on risk-adjusted returns. Our prior, however, is not supported whatsoever, as we see that including both variables has no effect on significance[12], resulting in a conclusion that quality and idiosyncratic volatility are both important to pricing but via independent channels.

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in the data), to control for serial correlation and demean the data to control for cross-sectional dependence. If no demeaning is performed, or no lags are included – the results remain virtually the same.

[12] Additionally we test an interaction variable between quality and volatility (unreported) and it comes out as highly insignificant, which further substantiates our conclusion.

Table 1

Panel Factor Model – Pricing Channels of Idiosyncratic Volatility and Quality

Dependent Variable: Quarterly Excess Returns

		I	II	III	IV	V
Const	coeff	-0.0002	0.0069	-0.0042	0.0048	-0.0051
	SE	0.0030	0.0043	0.0029	0.0041	0.0029
	pval	95.4%	11.3%	14.8%	23.8%	7.8%
IVOL	coeff	0.0332		0.0397		0.0378
	SE	0.0127		0.0129		0.0128
	pval	0.9%		0%		0.3%
Profita-bility	coeff				0.0328	0.0327
	SE				0.0046	0.0047
	pval				0%	0%
Growth	coeff				0.0271	0.0280
	SE				0.0032	0.0033
	pval				0%	0%
Safety	coeff				-0.0025	0.0081
	SE				0.0049	0.0040
	pval				61.1%	4.3%
Payout	coeff				0.0049	0.0048
	SE				0.0026	0.0025
	pval				5.6%	5.6%
Quality	coeff		0.0677	0.0783		
	SE		0.0065	0.0062		
	pval		0%	0%		
	Adj.R^2	15.13%	13.75%	15.81%	14.54%	16.33%
	N	86,629	86,629	86,629	86,629	86,629

Note. The dependent variable is the quarterly return in excess of risk-free rate. Explanatory variables are – idiosyncratic return volatility, *IVOL*, as defined in Section 5.3, and AFP (2013) quality score components, as defined in Section 5.2. Reported estimates are from a panel factor regression, with standard errors double-clustered by time and firm dimensions. *coeff* indicated the obtained point estimate, *SE* – standard error and *pval* – corresponding p-value. The table reports the effects of main variables on risk-adjusted return (alpha). To address non-synchronicity in reporting all market data (returns, factors and idiosyncratic volatility) are leading by one time period (quarter) relative to quality measurements.

The fact that there is a strong positive relationship between volatility and returns is consistent with the theories by Merton (1987) and Malkiel and Xu (2002). The theories conclude that if for various reasons there exists systematic under-diversification among market agents, some part of idiosyncratic risk becomes impossible to eliminate and hence it is rewarded. Also, a positive coefficient on volatility indirectly means that our measurement reflects a long- rather than short-term risk component, as the latter tends to be priced negatively (Xu & Cao, 2010).

6.2.1 Robustness Check of Pricing Channels

As a robustness check, we want to directly see whether quality can be transmitted into returns via idiosyncratic volatility that it might causes. To research the question we use methodology by Chua, Goh and Zhang (2006) adjusted for our purposes, as outlined in Section 5.4.1.

Table 2

Pricing Channels Rosbustness Check

Dependent Variable: 4 Factor Alphas		I	II	III	IV	V	VI
Const	coeff	0.0016	-0.0007	0.0006	0.0071	0.0005	0.0071
	SE	0.0025	0.0048	0.0047	0.0044	0.0047	0.0045
	pval	52.8%	89.0%	79.6%	10.8%	91.1%	11.5%
Quality-Predicted	coeff	0.0514			-0.0299		-0.0291
	SE	0.0122			0.0355		0.0372
	pval	0%			40.0%		43.3%
Volatility-Predicted	coeff		0.0595		0.0678		0.0685
	SE		0.0197		0.0380		0.0386
	pval		0.3%		7.4%		7.6%
Jointly-predicted	coeff			0.0547		0.0551	
	SE			0.0214		0.0201	
	pval			0.5%		0.6%	
Unexpected	coeff					0.0560	0.0559
	SE					0.0253	0.0249
	pval					2.7%	2.5%
	adjR2	0.59%	1.05%	0.92%	0.72%	1.43%	1.23%
	N	82,209	82,209	82,209	82,209	82,209	82,209

Note. The dependent variable is the alpha for a model with Fama-French (1993) and Carhart (1997) factors. Explanatory variables are – idiosyncratic return volatility, *IVOL*, as defined in Section 5.3, and AFP (2013) quality score, as defined in Section 5.2. The table presents the influence of expected volatility on average daily risk-adjusted returns, recalculated for each quarter and expressed as quarterly figure by multiplying it with number of trading days in the respective quarter. The expectations are formed using past information on quality score (Specification I), past volatility (Specification II) and joint predictions (Specifications III-VI). Unexpected volatility is equal to the difference between expected (predicted) and realized volatility (for more detailed explanation turn to section 5.4.1). Reported estimates are from a panel factor regression, with standard errors double-clustered by time and firm dimensions. *coeff* indicated the obtained point estimate, *SE* – standard error and *pval* – corresponding p-value.

In the first step, for each stock we estimate in-sample forecasts of idiosyncratic volatility based on lagged quality (Specification I), lagged idiosyncratic volatility (Specification II), joint prediction by both lagged idiosyncratic volatility and quality (Specification III) and separated quality and idiosyncratic volatility components from a joint estimation (Specification IV), all presented in Table 2. In second part we regress these ex-ante expectations on alphas from 4-factor model, calculated for each quarter using daily frequency. This allows us to see, whether quality-caused (expected) idiosyncratic volatility affects stocks' risk-adjusted performance.

The results show a significantly positive relation between quality-induced volatility and alphas. This, result, however should be taken cautiously, as forecasted volatilities in Specifications I and II have correlation of 81%. Since from Specifications II and III we see that the joint prediction decreases estimates both in magnitude and significance, this supports that different measures could have different coefficients. As a result we move towards decomposed (controlled) Specifications IV and VI. In these cases we see that effect of quality caused volatility is negative, however statistically insignificant – this works as a confirmation that quality has a very little impact on (expected) priced volatility. Comparing our results with findings of Chua, Goh and Zhang (2006) we find that the results are in line, as Specification V shows –– we also find that expected (jointly predicted) and unexpected volatility are both positively and significantly related to the returns.

To conclude, here we show that both quality and idiosyncratic volatility are positively related to risk-adjusted returns. Also, we document that the pricing of idiosyncratic volatility is robust to controlling for forecasted values based on prior quality and idiosyncratic volatility, suggesting that idiosyncratic volatility and quality are priced entirely through different channels. The robustness check confirms initial findings; in addition we also observe that it is unexpected volatility part of idiosyncratic volatility that is likely to be priced, while quality is likely to be related to the unpriced part.

6.3 Quality Scores and Idiosyncratic Volatility on Firm-Level Data

In the previous section we show that quality and idiosyncratic volatility are both priced, however, through entirely different channels. Nevertheless, the relation between them is worth a more thorough investigation, as our data shows that idiosyncratic volatility is positively priced, and therefore any systematic way to control this exposure could serve, for instance, as a basis for asset allocation in order to achieve desired level of risk-return trade-off. As stipulated by *Hypothesis 2* our initial expectation is that fundamentals should have a negative effect on the idiosyncratic volatility; Table 3 reports the estimates of the relationship.

Specifications I through IV report the coefficients from regressions of the firm-specific risk measure on the quality sub-scores. All 4 of them, *profitability, growth, safety* and *payout,* are negatively related to idiosyncratic return volatility, with the estimated coefficients being strongly significant at conventional levels. The estimates vary from -.267 for *safety* to -.065 for *growth* but, nevertheless, all of them are economically significant as well. For instance, a one standard deviation increase in *safety* decreases the expected level of idiosyncratic return volatility by 0.10, which is 37% of the time-series and cross-sectional average value (.2744). Three out of four dimensions of the *quality score* remain significant even when all of them are estimated in one equation, as Specification VI shows. The coefficients become smaller in magnitude but this decline is rather marginal for *safety*, meanwhile *growth* and *payout* decline almost by half and *profitability* loses its significance. The latter observation is a natural consequence of construction of *growth* proxy as 5-year changes in the *profitability* measurements and resulting rather high correlation between them (0.46; see Appendix H for correlation structure). However, relatively high robustness of the coefficients indicates that at least 3 out of 4 quality dimensions account for different variation in the idiosyncratic volatility.

Table 3

Relationship between Idiosyncratic Volatility and Quality components

Dependent Variable: Idiosyncratic Return Volatility							
		I	II	III	IV	V	VI
Const	coeff	0.2881	0.2743	0.2677	0.2758	0.2823	0.2700
	SE	0.0158	0.0148	0.0145	0.0149	0.0153	0.0148
	pval	0%	0%	0%	0%	0%	0%
Profita-bility	coeff	-0.1286					-0.0129
	SE	0.0154					0.0166
	pval	0%					44%
Growth	coeff		-0.0649				-0.0329
	SE		0.0093				0.0091
	pval		0%				0%
Safety	coeff			-0.2665			-0.2533
	SE			0.0240			0.0247
	pval			0%			0%
Payout	coeff				-0.0474		-0.0208
	SE				0.0100		0.0088
	pval				0%		0%
Quality	coeff					-0.2952	
	SE					0.0266	
	pval					0%	
	Adj.R^2	0.93%	0.38%	4.20%	0.18%	2.42%	4.35%
	N	88,378	88,378	88,378	88,378	88,378	88,378

Note. The dependent variable is the idiosyncratic return volatility, *IVOL*, as defined in Section 5.3; explanatory variables are AFP (2013) quality score components, as defined in Section 5.2. Reported estimates are from a panel factor regression, with standard errors double-clustered by time and firm dimensions. *coeff* indicated the obtained point estimate, *SE* – standard error and *pval* – corresponding p-value. To address non-synchronicity in reporting all market data (returns, factors and idiosyncratic volatility) are leading by one time period (quarter) relative to quality measurements.

Specification V shows how the aggregate total *quality score* fares in explaining idiosyncratic volatility – it is highly significant with estimated coefficient of -.295. The effect is also economically significant as well – a one standard deviation increase in *quality score* (0.27) would result into a 0.081 decline in idiosyncratic volatility, which is ca. 30% of the average value. Therefore, firm-level data allow to fully accept *Hypothesis 2* in that quality is negatively related to idiosyncratic return volatility.

6.4 Quality Measurements, Idiosyncratic Volatility and Returns

While *quality score* is a sufficiently good aggregated stand-alone measure to explain variation in idiosyncratic volatility and uncover the pricing channels of the two, due to its aggregate nature it is impossible to state what the driving force behind the relationship is. Therefore we disentangle the quality sub-scores into their components and find that coefficients on constituents are not monotonic and thus the aggregate quality sub-scores, both in terms of pricing and association with idiosyncratic volatility, are driven by a dominant set of variables, which we explore next.

6.4.1 Profitability Measurements

Panel A of Table G1 (Appendix G) reports that of 5 *profitability* measurements only 2 are statistically significantly related to idiosyncratic return volatility at acceptable levels – Return on Assets (ROA) and Gross Profit over Assets (GPOA). Interestingly, while both are meant to measure profitability, they have opposite effects on idiosyncratic volatility – ROA has negative and GPOA – positive. We reconcile it by the fact that while ROA is purely a profitability measure, GPOA measures earning capability. As a result it appears feasible that management of a firm with higher earnings capability on the top line (gross profit) can allow itself to be more inefficient on the middle lines of the income statement, therefore increasing the firm-specific risk (an argument that extends into *payout* dimension; see Section 7.2). Overall, negative relation of firm-specific risk with *profitability* appears to be mostly driven by ROA and the effect is large: a one standard deviation increase in ROA (0.65) reduces expected average idiosyncratic volatility by 0.13, which is 48% of the time-series and cross-sectional average. Table F2 (Appendix F) reports that pricing of *profitability* is also driven by ROA and GPOA – both are priced positively; the effect is also economically sizeable – a one standard deviation increase in ROA (GPOA) results into 1.65% (1.41%) increase in expected quarterly risk-adjusted return. Unexpectedly, we also report that low accruals (ACC) and higher gross margin (GMAR) result into economically small negative premium. When implications of *profitability* measurements and idiosyncratic volatility on returns are considered together the estimates remain largely the same, implying independent pricing.

6.4.2 Growth Measurements

Panel B of Table G1 (Appendix G) reports driving factors behind the *growth*-idiosyncratic volatility relationship. Three of them – ΔROA, ΔROE and ΔGMAR – are statistically significant and have a negative relation with idiosyncratic volatility. The strongest driver is ΔROA, closely followed by ΔGMAR. However, their economic significance is lower than that of *profitability*; a one standard deviation increase in ΔROA (ΔGMAR) reduces average expected volatility by 11% (8%) of cross-sectional and time-series average. In terms of pricing of *growth* constituents, Table F2 (Appendix F) reports that – ΔROA and ΔROE have a positive effect on pricing with the former having the strongest impact – a one standard deviation (.7824) increase in it results into 2.0% increase in quarterly risk-adjusted return. Interestingly, when *growth* measurements and idiosyncratic volatility are considered together ΔGPOA also becomes a positive determinant of risk-adjusted returns, however, its economic significance is very low.

We find ΔROA to be the strongest and most consistent driver behind pricing of *growth* and its relation to idiosyncratic risk; nevertheless, both are still priced through different channels.

6.4.3 Safety Measurements

Panel A of Table G2 (Appendix G) reports the relation between measurements of *safety* and idiosyncratic return volatility and shows that all 5 variables are statistically significant. At the same time, Table F3 (Appendix F) documents that three of them – both probabilities of remaining solvent (O- and Z-Scores) and earnings volatility (EVOL) – are significantly related to risk-adjusted returns. Firstly, of the three the largest expected premium commands Ohlson's O-Score – the probability of a firm remaining solvent; a one standard deviation increase implies 1.41% higher quarterly risk-adjusted return. However, the association with bankruptcy risk is unclear as the estimate on Altman's Z-Score is negative, although its impact on the premium is smaller in magnitude. Therefore, this leaves us with unexpectedly mixed evidence; however, we favour O-Score explanation, as it is based solemnly on fundamentals, unlike Z-Score which also incorporates the market valuation of equity, thereby combining several effects into one mixed measurement. Hence, based on evidence provided by O-Score we conclude that the solvency premium might be driven by flight to safety behaviour in the market – in downturn periods safety might be more valued by investors, which drives the risk-adjusted returns. Also we document a negative relation between O- and Z-Scores and idiosyncratic volatility which suggests that solvent firms have higher capital buffers to absorb any adverse shocks and better equity regeneration capacity to faster overcome them. The relationship between *safety* and idiosyncratic volatility is driven by O-Score - a one standard deviation increase reduces average expected idiosyncratic volatility by 57% of time-series and cross-sectional average.

Secondly, we document that earnings volatility (EVOL) is positively related to firm-specific risk, which goes in line with the prior that highly volatile (in terms of earnings) firms have higher specific risks. We also show that such firms earn higher risk-adjusted returns; this goes against our prior, as we would expect better quality (i.e. lower earnings volatility) to earn a premium. However, the finding is in line with the general risk-return framework, namely that higher risk (in this case approximated by higher earnings volatility) requires proper compensation.

All in all we conclude that prices seems to underreact to changes in the *safety* fundamentals, thereby driving idiosyncratic volatility; however, there is no consensus among investors what effects those changes should have on prices, therefore, the pricing implications of *safety* are poor.

6.4.4 Payout Measurements

Panel B of Table G2 (Appendix G) presents the estimated relation between *payout* measurements and idiosyncratic volatility. We expect a negative relation – higher payout increases efficiency of cash usage in the firm and hence reduces the idiosyncratic risk. And we observe it for equity-related payout variables – stock repurchase (EISS) and net payout of profits (NPOP). For debt-related payout (DISS) we document that deleveraging leads to higher idiosyncratic volatility, which is in line with the positive estimate on the Low Leverage variable (increase in LEV variable by construction means declining leverage). Overall, among *payout* measurements NPOP has the strongest effect on idiosyncratic volatility – a one standard deviation increase in the variable reduces average expected idiosyncratic volatility by 12.1% of the average value. In terms of pricing, DISS is the only variable having a consistent positive effect on risk-adjusted returns – a standard deviation increase in it leads to 0.43% higher quarterly risk-adjusted return, although we find a weak positive relationship between returns and equity redemption as well.

6.4.5 Pooled Specifications

To further investigate the strength of the relations outlined above, we consider all measurements together in one specification. Table G3 (Appendix G) reports the estimates for idiosyncratic volatility-quality relation and Table F5 (Appendix F) presents the pricing effects. We observe that in terms of idiosyncratic volatility determination all fundamental measurements retain significance of their estimates, which generally fall in magnitude, except the case of ΔROA which also reverses the sign, which we attribute to high correlation between ΔROA and ROA of .61. In terms of effect of fundamental measurements on risk-adjusted returns, we document that the most robust quality dimensions are *profitability, growth* and *payout*, as the estimates within them remain significant and affect returns in the same direction. *Safety* dimension is the noisiest and weakest of all, with most of measurements changing their signs or significance, which could be attributed to rather high correlation with other dimensions, particularly of O- and Z-Scores. Thus, on the fundamental measurement level we conclude that *growth*, *safety* and *payout* constituents are strong determinants of level of idiosyncratic risk, and *profitability*, *growth* and *payout* are significantly related to risk-adjusted returns. However, we document that due to very aggregate nature of the AFP (2013) *quality score* construction (i.e. averaging 18 fundamental measurements), the underlying economic mechanism behind its association with returns and idiosyncratic volatility is quite difficult to pinpoint with high degree of certainty; rather we present evidence that all measurements contribute partially to the score, making it measure the aggregate quality of a stock, as it is expected to do.

Pooled regressions with all fundamental quality measurements also allow to conclude that in terms of explaining idiosyncratic volatility, quality score fares relatively well and produces adj. R^2 from regression with 4 quality sub-scores of 4.35% and from regression with *quality score* of 2.42%; however, individual measurements are substantially more successful in accounting for firm specific risk – all 18 fundamentals yield adj. R^2 of 14.38%. In terms of pricing, the conclusion is more favourable of quality score – adj. R^2 from regressions with quality sub-scores is ca. 15% and from regression with 18 fundamentals – ca. 18%. Therefore, we conclude that for pricing implications quality sub-score are fair to employ, while for determining idiosyncratic return volatility – individual measurements are of better use.

7 Discussion

The primary goal of this paper is twofold – to investigate how stock quality and idiosyncratic volatility are priced jointly (and primarily – to check if idiosyncratic volatility is just a pricing channel for quality) and to explore the relation between the two. This section, first, presents and discusses the implications of our findings on the stand-alone *quality score* level and second elaborates on the fundamental drivers of the relationship.

7.1 General Quality-Idiosyncratic Return Volatility Relation

The motivation for this paper came from several puzzling relationships that had a potential of being a different side of the same coin. On one hand, we have a broad debate on whether idiosyncratic volatility can be priced and if it is, does it earn a positive or a negative premium. The observed pricing relationship in the literature would then in turn imply that conventional pricing models (i.e. four factor model used in this paper) is not a good proxy for a true but unobservable asset pricing model. On the other hand, we have a recent AFP (2013) paper which argues that stock quality, defined by fundamental variables of the underlying companies, could be a valuable adjustment for an asset pricing model – the authors conclude that quality-minus-junk (QMJ) is a robust cross-sectional factor. As a result we attempt to connect classical empirical risk-return trade-off with the fundamental quality approach.

As quantification of risk and return relationship has dominated mainstream literature for decades dealing with the classical measures used in the paper is based on plentiful guidance from the past research. Operationalization of the quality dimension, however, is a much less explored ground. We chose AFP (2013) framework, as it uses an extensive list of fundamental variables that cover all of the quality dimensions and summarizes it in one number – a favourable quality in line of conventional asset pricing theory. Also, this way we do not disregard potentially important fundamental features, which might be an issue if a less comprehensive quality definition is used (e.g. quality of earnings only). The main delimitation of this approach is (as we show with the analysis of constituents of the score discussed in the last section) that some quality dimensions are, in fact, more important than others, and therefore simple equally-weighted proxy of quality is rather noisy. Although finding a more appropriate definition of quality is beyond the scope of this paper, we believe that our findings could assist further research with the respect to this issue.

While researching our *Hypothesis 1*, we document a number of different findings. Firstly, we explore how firm's quality interacts with risk-adjusted performance (alphas) and whether relationship between volatility and alphas changes when quality is included. What we find is that generally idiosyncratic volatility affects risk-adjusted performance positively and we argue that this affect is likely due to unexpected volatility. Also we see strong evidence that good quality stocks earn substantially higher returns. Finally, when we include quality in the regressions, we observe that both quality and idiosyncratic volatility maintain their signs and significance. This suggests that the priced component of idiosyncratic volatility and quality does not represent the same underlying factor, resulting into the rejection of *Hypothesis 1*.

We then proceed to the analysis of idiosyncratic volatility-quality relationship by exploring our *Hypothesis 2*. The importance of this relationship is apparent when combining findings of Campbell et al (2001) and Goetzmann and Kumar (2008) that suggest people to be highly undiversified in a time when diversification benefits increase. Irrespective of the reasons for poorly diversified portfolios, knowing whether fundamental features affect idiosyncratic volatility could help investors make better decisions on portfolio allocations to different assets. Here we provide some interesting insights as well. Firstly, in support of *Hypothesis 2* we do find evidence that firm-specific volatility is a negative function of quality which means that by picking stable high-quality firms undiversified investors would be left off with smaller amount of risk. Secondly, we confirm a delimitation of aggregate quality score being noisy by outlining that volatility can be explained substantially better when disaggregated quality components are used.

All in all, the findings tell a somewhat unexpected story. By holding good quality stocks investors are expected to earn a higher risk-adjusted premium and also to hold less idiosyncratic risk. However, since we have seen that idiosyncratic volatility and quality do not interact in pricing, this implies that quality reduces unpriced part of firm-specific risk. Although these findings call for further investigation, one of possible explanations is that quality becomes more important at the times of turmoil, i.e. it works as a fundamental hedge in market downturns and thus creates flight to quality. As we show in Panel F in Appendix C for aggregate quality and idiosyncratic volatility indices, in times of high volatility the gap between average value- and equally-weighted quality increases, while on the other hand the idiosyncratic risk for value-weighted index remains moderate compared with equally-weighted case. This allows to reconcile our findings in the following way. Firstly, when market starts to panic investors look for stocks that could maintain their performance as well as provide as low idiosyncratic volatility as possible. As a result, extra demand for high quality stocks occurs, which in turn drives market capitalization of these stocks (and value-weighted quality index). This creates grounds for abnormal returns on good quality stocks from both the fact that low quality stocks handle crises poorly and extra demand created by flight-to-quality, thus enhancing the positive quality-return relationship. Secondly, due to the fact that in extreme periods high quality stocks tend to maintain their idiosyncratic risk at relatively stable levels, whereas low quality stocks' firm-specific risk boosts is a confirmation of negative quality-volatility relationship. Finally, the fact that quality and volatility are priced independently could work in line of Malkiel and Xu (2002) argument – due to the fact that some of idiosyncratic risk cannot be diversified, because of investors' limited access to different assets, it asks for a reward. In turn, independence of pricing channels would mean that even though there is a negative relationship between quality and volatility, these effects work only with the part of idiosyncratic volatility that still can be diversified. To conclude, this would suggest that quality is a strong measure of counter-cyclicality, and selecting a portfolio of high quality stocks before high volatility periods is a potentially profitable (on risk-adjusted basis) strategy.

Another potential rationalization of our findings could be related to the concept of long- and short-term idiosyncratic volatility. As Xu and Cao (2010) argue idiosyncratic volatility has two components – long-run volatility, which is priced positively due to theoretical considerations provided by Malkiel and Xu (2002), and short-term volatility that introduces cost of arbitrage and induces a negative volatility-return relationship (Stambaugh, Yu & Yuan, 2013). To match the frequencies between quality and idiosyncratic volatility in our work we are forced to use a volatility measure that is taken from a relatively long window (quarter) and hence it is likely to load more on the long-run component (coefficients on idiosyncratic volatility are consistent with such statements). As such short-term volatility component plays a minor role in this measurement. Nevertheless, quality pricing still could be driven by its interaction with arbitrage-limiting volatility. In our findings, the fact that quality is able to explain only a small (but significant) fraction of the volatility, then, would reflect the feature that our idiosyncratic volatility measure is dominated by the long-term component. Secondly, if quality's negative impact on volatility relates only to negatively priced volatility, we expect it to be priced positively (which is consistent with our results) and the slight increase in both idiosyncratic volatility and quality coefficients in return regressions could be explained as controlling effects – negative pricing effects in volatility become positive effects in quality. To sum up, that would mean that stocks with better fundamentals have a lower dispersion of opinion and as a result do not suffer from severe over-pricings present in lower-quality stocks. Since these overpricing induces negative patterns in returns we see good quality stocks over-performing poor-quality ones.

7.2 Drivers Behind Quality-Idiosyncratic Volatility Relation, and Pricing of Thereof

As we have already discussed, *quality score* due to APF is a convenient solution to operationalize fundamental attractiveness of a stock. However, due to its aggregate nature, the exact mechanism driving *quality score's* pricing and association with idiosyncratic volatility cannot be established with certainly. Therefore, in this section we again disentangle the *score* into separate fundamentals and analyse which of them are driving quality and what the resulting implications are.

First, we document a strong negative relation of *profitability* to idiosyncratic risk and positive effects on risk-adjusted returns of both. This implies that higher *profitability* results into lower idiosyncratic volatility which in turn is positively priced, hence more lucrative businesses are expected to have higher returns through quality channel. It also results into a negative impact on returns coming from higher quality leading to lower firm-specific volatility that is positively priced; therefore quality cannot be incorporated into prices through idiosyncratic volatility channel. This is generally supportive of the Irvine and Pontiff (2009) competition explanation – firms with higher market power (lower competition and hence wider profitability margins) are more profitable and tend to outperform less competitive peers which results into an under-priced return effect; in addition, when higher profitability and market power comes at the expense of other firms this introduces negative covariance between returns of more and less competitive firms – hence the negative relation of *profitability* with idiosyncratic volatility. Overall, with existing evidence at hand, we tend to conclude that *profitability* dimension of quality, constructed using APF methodology, is extremely noisy, and is perhaps the weakest of the 4, as also illustrated in Specification IV, Table 3, where profitability loses its significance when considered together with other dimensions as a determinant of idiosyncratic volatility.

Second, we document a negative relation between *growth* and idiosyncratic volatility, as well as positive effect on risk-adjusted returns of both, also suggestive of pricing through different channels. Interestingly, the negative relation to firm-specific risk in our findings is opposite of those in the existing literature. Theoretically, growth should be positively related to idiosyncratic return volatility, as equity of younger firms, which have high realized growth, represents a claim on cash flows that occur further in the future and thus are associated with higher uncertainty. Previous studies have mostly focused on the firm age and firm age at IPO, while we use different *growth* proxies, namely 5-year changes of profit, cash flow and accruals margins. Therefore, we reconcile our findings with the literature, firstly, by the fact that *growth* in the AFP framework rather approximates changes in the earning capacity and hence more of a measure of earning capability and profitability. As a result, we observe that firms that have managed to increase their profitability over the past years substantially have lower firm-specific risk. Secondly, the growth measurements that we employ are rather long term – 5 years – which might be a sufficiently long period for the documented age effect to wear off.

Third, we document a negative relation between *safety* and idiosyncratic volatility, substantiating the fundamental view that safer firms should have lower risk than the market. Our results show that firms with healthier capital structure, i.e. those that can absorb larger market or operational shocks, are perceived more stable by investors and hence command lower idiosyncratic volatility. Similarly, firms that promise higher probability of returning committed capital, i.e. those being characterized by lower earnings volatility, have lower investment risk which translates into investors perceiving them as safe and thus having lower idiosyncratic volatility. We also show that firms whose systematic risk is considered by investors to be low (i.e. low market beta) also command lower idiosyncratic risk. At the same time, while given a strong negative relation of *safety* to firm-specific risk, *safety* dimension of quality appears not to impact strongly risk-adjusted returns. Thus, it seems that stock prices do react to changes in fundamentals, thus driving idiosyncratic volatility, however there is no consensus among investors on how to interpret these changes, therefore no return effect is observed.

Fourth, in line with initial expectations the relation between equity-related *payout* and idiosyncratic volatility is negative. This illustrates the Jensen's (1986) managerial incentive argument: the firms that return more funds to the shareholders, and subsequently are under pressure to make more efficient capital allocations, commit less capital to potentially low yielding or even unprofitable projects; as a result such firms are less risky and have lower idiosyncratic volatility. In line with initial expectations we find that *payout* through share repurchases (EISS) is positively related to risk-adjusted returns, indicating that a repurchases of stocks signals managements' conviction that it is undervalued, which is positively perceived by investors and as a result translates into positive impact on returns. In addition, we document intriguing findings with respect to debt retirement that is unexpectedly positively related to idiosyncratic volatility. We combine it with similarly seemingly puzzling finding the leverage is negatively associated with idiosyncratic volatility and indirectly relate both also to Jensen's (1986) argument[13] – higher

[13] By extension we also argue that higher profitability on the top line, e.g. GPOA, results into higher potential for the management to be inefficient in the middle lines of the income statement, which might lead to ineffective

leverage puts more pressure on the management to make efficient allocation of available recourses; hence reducing leverage might in fact lead to less efficient capital allocations and hence to higher idiosyncratic return volatility. We also document that investors require a positive premium on the stocks of firms conducting higher debt redemptions, indicating that investors need compensation for holding this risk. In addition, it also makes sense on accounting grounds, as firms with lower debt pay less in interest expenses, hence become more profitable thus boosting returns to shareholders.

All in all, we document three robust channels that relate quality and idiosyncratic volatility and make the former a priced feature. First, there is the competition argument, implying increasing competition leading to lower returns and higher idiosyncratic volatility through profitability. Second, higher ability and improvement in it to generate new equity (through higher or improving earnings capacity) also reduces firm-specific risk and while making capital structure more sound leads to positive returns, in line with the argument described previously. Lastly, we also document that higher risk of inefficient management (or elevated issues with mixed managerial incentives) translates into higher firm-specific volatility, and thus necessitates investors to demand a premium for holding it. This number of mechanisms allows to streamline portfolio allocation approaches particularly for under-diversified investors by either focusing on maximization of return by holding higher quality assets, or minimization of firm-specific risk by choosing portfolio mix based on those fundamentals that allow to minimize such exposure.

8 Conclusion

In this paper we set to investigate two pricing effects that go against modern generally accepted asset pricing models. The first one relates to a sizable body of existing literature which has established that idiosyncratic return volatility is in fact a priced feature of stocks, unlike the standard models predict. While the exact pricing mechanism is not yet established, arguments and evidence for both negative and positive premiums exist, we document that idiosyncratic return volatility is positively priced with the effect being substantial – a standard deviation increase in the firm-specific risk measurement is expected to boost risk-adjusted returns by 1.73% on quarterly basis. This finding is in line with Merton (1987) and Malkiel and Xu (2002) under-diversification argument, which suggest that under-diversification is a systematic phenomenon that makes some part of idiosyncratic risk impossible to diversify which grants it a positive premium.

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spending or allocation of capital to inefficient projects, which thereby increases the risks. Thus, the higher is probability of the management to be inefficient the higher we expect idiosyncratic volatility to be.

The second line of novel literature providing challenging findings to the existing pricing models is that a quality of a stock, as measured by a selection of fundamental variables, is also a determinant of expected returns. We find that stocks with higher *quality score*, constructed using Asness, Frazzini and Pedersen (2013) methodology, are expected to earn a sizable premium – a one standard deviation higher *quality score* results into 2.15% boost in risk-adjusted quarterly return. This substantiates the explanation that investors typically under-react to changes in the fundamentals, which allows firms with better fundamentals to earn a premium. Pricing of quality is driven by a selected set of fundamental measurements, mostly related to *growth*, *profitability* and *payout* characteristics of a stock, largely backed by fundamental explanations. For instance, a stock with higher volatility of earnings promises less certainty to return invested capital over short term and thus offers investors a premium to compensate for elevated risk.

So, if the reason for pricing of quality is systematic under-reaction to changes in fundamentals, then the very same under-reaction should also be reflected in the stock idiosyncratic volatility. Hence, we attempt to reconcile the two puzzling lines of literature, by postulating that pricing of idiosyncratic volatility is merely a channel for pricing of quality. However, in broad terms we do not find any support for the claim and conclude that the two are priced independently. We also acknowledge that our idiosyncratic volatility measure is of a long-term nature and, as existing literature indicates, such volatility is priced positively. However, we also observe patterns which suggest that the measure could capture some negatively priced short-term idiosyncratic volatility, which constrains arbitrageurs and this way creates stronger under-reaction. Patterns in our estimates allow us to argue that quality is related to this short-term component, and given a negative relation between idiosyncratic volatility (in general) and negative pricing of short term idiosyncratic volatility documented in existing literature, the effect of better quality through this channel on returns in positive. Therefore, we provide some indirect evidence that a minor portion of volatility can be priced-in though the short-term idiosyncratic volatility channel. However, data frequency of quality measurement and consequent necessity to employ a long-term proxy for the idiosyncratic volatility measure do not allow for direct testing of this proposition.

Given that idiosyncratic volatility is a priced feature, one would want to control for such exposure, particularly in under-diversified portfolios. For this purpose, we investigate whether quality can be used to determine expected idiosyncratic volatility; in fact, we document a very strong negative relation between the two – a stock with a standard deviation higher *quality score* is expected to have idiosyncratic volatility that is lower by 30% of the cross-sectional and time-series average. The relation is primarily dominated by selected *growth, safety* and *payout* characteristics of a stock, all backed by fundamental explanations. For instance, a stock with lower bankruptcy risk is in possession of a more solid capital structure which has higher capacity to absorb any operational or external shocks, therefore its riskiness is lower and thus idiosyncratic volatility is lower as well.

All in all, we empirically show that idiosyncratic return volatility and quality are both priced positively and independently from each other, with minor indirect evidence that a small portion of firm-specific volatility can serve as a pricing channel for quality. We believe that our findings are of most relevance for portfolio construction, as using the *quality score* does allow to manipulate the expected exposure to idiosyncratic return volatility, as well as to earn an expected extra risk-adjusted return on high quality stocks, which can be particularly handy for under-diversified retail investors. We document that for the purposes of utilizing pricing implications of quality, aggregate *quality score* and its dimensions are sufficiently good. However, if quality is to be used in order to devise an enhancement scheme for idiosyncratic volatility exposure the evidence shows that disaggregated fundamental measurements provide a better understanding of how that can be achieved. At the same time we do acknowledge that from the discussion of quality measurements and from some degree of inconsistency among variables meant to measure a certain dimension of quality it is apparent that Asness, Frazzini and Pedersen (2013) *quality score* has its shortcomings. However, primarily our goal was to test how it fares with respect to idiosyncratic volatility and its pricing, and not to construct a perfect quality measure. Therefore, if a trading strategy or a portfolio allocation approach is to be defined based on the findings, there is room for redefinition of variables and consequent enhancement of results.

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Appendix A: Definition of Quality Score Variables

This section is meant to elaborate on the construction of variables that later after standardization enter four dimensions of quality score and consequently the quality score itself. All of the variables below have been shown to be strongly related the performance of the stocks; for the complete list of sources documenting the relations please refer to AFP (2013). The variables are obtained from CRSP/Compustat merged database; the variable names refer to Compustat data items, except for primary items calculated from other data items; unless separately specified variables are contemporaneous values in period t. All data is in millions USD, except share count which is in millions.

Preliminary items

Minority interest (MIB): Primarily minority interest is taken as Total Minority Interest (MIBTQ), in case unavailable it is taken as Redeemable Minority Interest (MIBQ) or Non-Redeemable Minority Interest (MIBNQ).

Preferred Stock (PTSK): Similarly, preferred stock is calculated as Preferred/Preference Stock (Capital) (PSTKQ); if unavailable it is taken as Redeemable Preferred/Preference Stock (Capital) (PSTKRQ) or Non-Redeemable Preferred/Preference Stock (Capital) (PSTKNQ).

Book Equity (BE): Book equity is calculated as Common/Ordinary Equity; if unavailable then it is calculated as the difference between Stockholders Equity (SEQ) and Total Preferred Stock (PSTKQ). If any data is still lacking to calculate book equity, then it is obtained as the difference between Total Assets (ATQ) and the sum of Total Liabilities (LTQ) and Minority interest (MIBQ).

Working Capital (WC): Primarily working capital is calculated as Total Current Assets (ACTQ) less Total Current Liabilities (LCTQ) less Cash and Short Term Investment (CHEQ) plus Debt in Current Liabilities (DLCQ) and plus Income Tax Payable (TXPQ) - ACTQ-LCTQ-CHEQ+DLCQ+TXPQ. If unavailable, we take balance sheet item – Working Capital (WCAPQ), which is poorly available. Change in working capital (ΔWC) is calculated as the difference in working capital balance between two quarters; if unavailable we use year-to-date data items Total Working Capital Changes (WCAPCHY) or Decline (Increase) in the Working Capital (UWKCAPCY), both transformed into quarterly frequency.

Number of Shares: For number of shares we use CRSP's data item – SHROUT.

Profitability

Profitability measures that enter the quality score calculation are the following standardized (z-scores) margins:

Gross Profit Over Assets (GPOA) is calculates as the difference between Total Revenue (REVTQ) and Cost of Goods Sold (COGSQ) divided by Total Assets (ATQ):

$$GPOA = \frac{(REVTQ - COGSQ)}{ATQ}$$

Return on Equity (ROE) is Income Before Extraordinary Items (IBQ) divided by Book Equity (BE):

$$ROE = \frac{IBQ}{BE}$$

Return on Assets (ROA) is Income Before Extraordinary Items (IBQ) divided by Total Assets (ATQ):

$$ROA = \frac{IBQ}{ATQ}$$

Cash Flow Over Assets (CFOA): we calculate cash flow as Income Before Extraordinary Items (IBQ) plus Depreciation (DPQ) less Change in Working Capital (ΔWC) less Capital Expenditures (CAPX) divided by Total Assets (ATQ):

$$CFOA = \frac{(IBQ + DPQ - \Delta WC - CAPX)}{ATQ}$$

Gross Margin (GMAR) is the difference between Total Revenue (REVTQ) and Cost of Goods Sold (COGSQ) divided by Total Revenue (REVTQ):

$$GMAR = \frac{(REVTQ - COGSQ)}{REVTQ}$$

Low Accruals (ACC) are calculated as the negative difference between Change in Working Capital (ΔWC) and Depreciation (DPQ) divided by Total Assets (ATQ):

$$ACC = \frac{-(\Delta WC - DPQ)}{ATQ}$$

Growth

Following AFP (2013) we calculate growth as the 5-year (20-quarter) change in the profit or cash flow measurement in the profitability measures, divided by 5-year lagged denominator (total assets, equity or sales):

$$\Delta GPOA_t = \frac{(REVTQ_t - COGSQ_t) - (REVTQ_{t-20} - COGSQ_{t-20})}{ATQ_{t-20}}$$

As long as we use quarterly data, we use 20-period lags to calculate changes over 5 years.

$$\Delta ROE_t = \frac{IBQ_t - IBQ_{t-20}}{BE_{t-20}}$$

$$\Delta ROA_t = \frac{IBQ_t - IBQ_{t-20}}{ATQ_{t-20}}$$

$$\Delta CFOA_t = \frac{(IBQ_t + DPQ_t - \Delta WC_t - CAPX_t) - (IBQ_{t-20} + DPQ_{t-20} - \Delta WC_{t-20} - CAPX_{t-20})}{ATQ_{t-20}}$$

$$\Delta GMAR_t = \frac{(REVTQ_t - COGSQ_t) - (REVTQ_{t-20} - COGSQ_{t-20})}{REVTQ_{t-20}}$$

$$\Delta ACC_t = \frac{\left(-(\Delta WC_t - DPQ_t)\right) - \left(-(\Delta WC_{t-20} - DPQ_{t-20})\right)}{ATQ_{t-20}}$$

Safety

Safety aggregate z-score is calculated as the average of standardized value of the following variables:

Betting Against Beta (BAB) in the negative value of the market beta of the stock. The beta is calculated following Frazzini and Pedersen (2013) methodology: it is the ratio of the product of rolling one-year (250 trading days) daily standard deviations (of the stock and the market) divided by the three-year (1250 trading days) three-day rolling correlation between them.

Low Leverage (LEV) is calculated as the negative sum of Long Term Debt (DLTTQ), Debt in Current Liabilities (DLCQ), Minority Interest (MIB) and Preferred Stock (PSTK), divided by Total Assets (ATQ):

$$LEV = \frac{-(DLTTQ + DLCQ + MIB + PSTK)}{ATQ}$$

Ohlson's O-score (O-Score) is calculated as:

$$OScore = -\Big(-1.32 - 0.407 * \ln\left({}^{ATQ}/_{CPI}\right) + 6.03 * \mathrm{TLTA} - 1.43 * \mathrm{WCTA} + 0.076 * \mathrm{CLCA} - 1.72 * \mathrm{OENEG} - 2.37 * \mathrm{NITA} - 1.83 * \mathrm{FUTL} + 0.285 * \mathrm{INTWO} - 0.521 * \mathrm{CHIN}\Big),$$

where CPI is US Consumer Price index issued by US Bureau of Labour Statistics and it is rebased to 100 in 1968, as in original Ohlson's (1980) paper. TLTA is the sum of Debt in Current Liabilities (DLCQ) and Long Term Debt (DLTTQ), i.e. book value of debt, divided by Adjusted Assets (ADJASSET):

$$TLTA = \frac{(DLCQ + DLTTQ)}{ADJASSET}$$

WCTA is the difference between Current Assets (ACTQ) and Current Liabilities (LCTQ) divided by Adjusted Assets (ADJASSET):

$$WCTA = \frac{(ACTQ - LCTQ)}{ADJASSET}$$

CLCA is the ratio of Current Liabilities (LCTQ) to Current Assets (ACTQ):

$$CLCA = \frac{LCTQ}{ACTQ}$$

OENEG is a dummy variable equal to 1 if Total Liabilities are larger than Total Assets:

$$OENEG = 1, if\ LTQ > ATQ$$

NITA in the ratio of Net Income (IBQ) tot Total Assets (ATQ):

$$NITA = \frac{IBQ}{ATQ}$$

FUTL in the ratio of Pretax Income (PTQ) to Total Liabilities (LTQ):

$$FUTL = \frac{PTQ}{LTQ}$$

INTWO is a dummy variable equal to 1 if current or prior period Net Income (IBQ) is negative:

$$INTWO = 1, if \min(IBQ_t, IBQ_{t-1}) < 0$$

CHIN is change in Net Income (IBQ) defined as:

$$CHIN = \frac{(IBQ_t - IBQ_{t-1})}{|IBQ_1 - IBQ_{t-1}|}$$

Altman's Z-Score (Z-Score), due to Altman (1986), is calculated as:

$$ZScore = \frac{(1.2 * WC + 1.4 * REQ + 3.3 * EBIT + 0.6ME + REVTQ)}{ATQ},$$

where WC is Working Capital, as defined above, REQ are Retained Earnings, $EBIT$ is Earnings Before Interest And Tax (OAIDPQ), ME is Market Value of Equity (Number of Shares times Closing Price for the reporting quarter) and $REVTQ$ is Total Revenue; ATQ are Total Assets.

Earnings Volatility (EVOL) is calculated as standard deviation of ROE over the past 20 quarters; we require at least 12 observations to exist, so that to calculate the measure.

Payout

Payout component of quality score is calculated as an average of standardized values of Net Equity Issuance (EISS), Net Debt Issuance (DISS) and Net Payout Over Profits (NPOP).

Net Equity Issuance (EISS) is the minus natural logarithm of the ratio of the contemporaneous split adjusted number of shares to corresponding value in the prior quarter:

$$EISS = -\ln\left(\frac{Adj.SharesOut_t}{Adj.SharesOut_{t-1}}\right)$$

Net Debt Issuance (DISS) is the minus natural logarithm of the ratio of Total Debt in the current period to the previous period. Total Debt is defined as the sum of Total Long-Term Debt (DLTTQ), Debt in Current Liabilities (DLCQ), Minority Interest (MIB) and Preferred Stock (PSTK):

$$DISS = -\ln\left(\frac{DLTTQ_t + DLCQ_t + MIB_t + PSTK_t}{DLTTQ_{t-1} + DLCQ_{t-1} + MIB_{t-1} + PSTK_{t-1}}\right)$$

Net Payout Over Profits (NPOP) is the sum of Net Payout over the past 20 quarters relative to total Gross Profit over the same period:

$$NPOP_{t+19} = \frac{\sum_{t=1}^{t=20}\left(IBQ_t - (BE_t - BE_{t-1})\right)}{\sum_{t=1}^{t=20}(REVTQ_t - COGS_t)}$$

By construction, i.e. due to making them negative, a change in EISS and DISS represents share and debt repurchases, respectively.

Appendix B: Descriptive Statistics

Table B1

Descriptive Statistics of Raw Quality Measurements

	Mean	St. Dev.	Min	Max	5%	95%	Variable Obs.	Firm-Quarter Obs.
A. Profitability Measurements								
GPOA	0.08	0.08	-0.19	0.34	-0.02	0.23	577,060	667,080
ROE	0.00	0.17	-1.06	0.60	-0.23	0.11	639,360	667,080
ROA	0.00	0.06	-0.33	0.08	-0.11	0.04	640,400	667,080
CFOA	0.00	0.11	-0.51	0.36	-0.19	0.13	226,290	667,080
GMAR	0.19	1.02	-8.22	0.91	-0.18	0.75	574,100	667,080
ACC	0.01	0.07	-0.28	0.29	-0.09	0.11	532,290	667,080
B. Growth Measurements								
ΔGPOA	0.10	0.23	-0.28	1.36	-0.08	0.53	378,690	667,080
ΔROE	0.01	0.24	-1.33	1.03	-0.24	0.26	440,010	667,080
ΔROA	0.00	0.09	-0.50	0.36	-0.11	0.12	424,080	667,080
ΔCFOA	0.01	0.20	-0.93	0.81	-0.28	0.29	83,953	667,080
ΔGMAR	0.51	1.60	-2.54	11.73	-0.37	2.48	383,490	667,080
ΔACC	0.01	0.14	-0.57	0.68	-0.17	0.21	317,380	667,080
C. Safety Measurements								
O-Score	-0.09	2.35	-8.81	4.99	-4.32	2.95	508,300	667,080
Z-Score	1.00	2.16	-11.74	4.68	-2.30	3.12	367,080	667,080
LEV	-0.24	0.22	-0.98	0.00	-0.65	0.00	551,950	667,080
EVOL	0.25	0.81	0.00	6.17	0.01	1.16	610,270	667,080
BAB	-0.90	0.58	-5.76	3.53	-1.97	0.13	501,560	667,080
D. Payout Measurements								
DISS	-0.02	0.36	-1.75	1.43	-0.52	0.41	469,330	667,080
NPOP	-0.06	1.07	-6.27	5.00	-1.05	0.77	522,190	667,080
EISS	-0.01	0.04	-0.27	0.07	-0.06	0.02	490,760	667,080

Note. All variables are as defined in Appendix A; descriptive statistics represent cross-sectional and time-series average values.

Table B2

Descriptive Statistics of Aggregate Quality and Volatility Measures

	Mean	St. Dev.	Min	Max	5%	95%	Periods	Average numb. of firms in a period
A. Equally Weighted Average Indices								
Profitability	0.06	0.02	-0.01	0.12	0.03	0.09	132	1,379
Growth	0.00	0.02	-0.05	0.04	-0.03	0.03	132	1,379
Safety	-0.06	0.02	-0.11	-0.02	-0.09	-0.03	132	1,379
Payout	0.01	0.02	-0.02	0.07	-0.01	0.05	132	1,379
Quality	0.00	0.01	-0.01	0.03	-0.01	0.02	132	1,379
IVOL	0.33	0.18	0.11	0.94	0.13	0.67	132	1,379
B. Value Weighted Average Indices								
Profitability	0.20	0.06	0.06	0.33	0.10	0.30	132	1,379
Growth	0.13	0.14	-0.06	0.72	0.01	0.47	132	1,379
Safety	0.11	0.08	-0.07	0.27	-0.04	0.24	132	1,379
Payout	0.05	0.05	-0.10	0.14	-0.06	0.12	132	1,379
Quality	0.13	0.06	0.01	0.32	0.04	0.21	132	1,379
IVOL	0.08	0.05	0.03	0.30	0.04	0.17	132	1,379

Note. *Profitability*, *Growth*, *Safety* and *Payout* refer to quality subscores, *Quality* refers to total quality score as defined in Appendix A; *IVOL* refers to idiosyncratic return volatility, as defined in Section 5.3.

Table B3

Descriptive Statistics of Standardized Quality Measurements

Variable	Mean	Std. Dev.	Min	Max	5%	95%	Obs.
A. Idiosyncratic Return Volatility							
IVOL	0.2744	0.5208	0.0000	14.5920	0.0177	1.0619	88,378
B. Quality (Sub)indices							
Profitability	0.1062	0.3915	-4.6304	2.1985	-0.4255	0.6435	88,378
Growth	-0.0023	0.4975	-4.6538	7.4549	-0.5091	0.7856	88,378
Safety	-0.0251	0.4004	-3.1515	2.1595	-0.7434	0.5571	88,378
Payout	0.0284	0.4696	-5.5894	3.6628	-0.8028	0.5534	88,378
Quality	0.0268	0.2745	-2.4377	2.4284	-0.4167	0.4271	88,378
C. Profitability Measurements							
GPOA	0.0788	0.8176	-3.5766	3.7687	-0.8528	1.6133	88,378
ROE	0.1013	0.7596	-9.6427	5.5353	-0.6529	0.6077	88,378
ROA	0.1952	0.6541	-7.5617	3.5193	-0.7117	0.8117	88,378
GMAR	0.1100	0.4533	-9.5403	3.1409	-0.1305	0.4848	88,378
ACC	0.0457	0.8153	-5.5462	5.4990	-1.0606	1.1687	88,378
D. Growth Measurements							
ΔGPOA	-0.0314	0.8116	-2.5316	10.3260	-0.6705	1.2891	88,378
ΔROE	0.0380	0.8377	-10.1600	7.8433	-0.7403	0.9314	88,378
ΔROA	0.0441	0.7824	-10.1350	8.1073	-0.8018	1.0327	88,378
ΔGMAR	-0.0587	0.7479	-3.9108	16.0420	-0.4367	0.7747	88,378
ΔACC	-0.0035	0.8460	-5.7090	6.8710	-1.0875	1.1562	88,378
E. Safety Measurements							
EVOL	-0.2419	0.8705	-3.8696	1.6055	-1.7750	0.9496	88,378
O-Score	-0.1259	0.7334	-0.3460	12.2080	-0.3265	0.3153	88,378
Z-Score	0.1111	0.8387	-5.5354	2.7236	-1.3807	1.2174	88,378
BAB	0.1080	0.6860	-8.8398	3.3208	-0.9340	0.9702	88,378
LEV	0.0232	0.9132	-5.7789	5.0997	-1.6493	1.2734	88,378
F. Payout Measurements							
DISS	0.0082	0.8524	-6.7706	5.8443	-1.0808	0.9195	88,378
EISS	0.0410	0.8814	-10.8770	3.0692	-0.8338	0.6240	88,378
NPOP	0.0360	0.6140	-6.3000	10.7120	-0.4585	0.3615	88,378

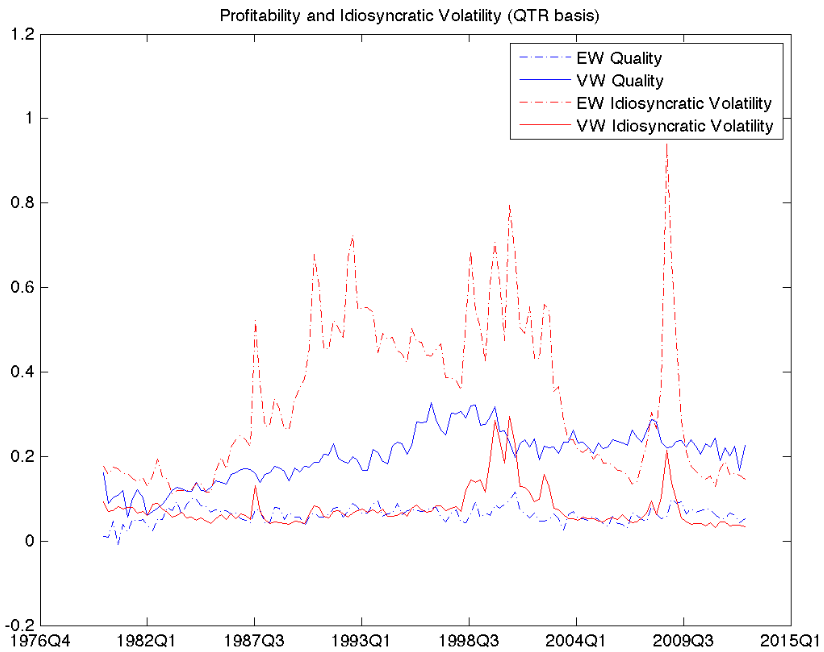
Note. *Profitability*, *Growth*, *Safety* and *Payout* refer to quality subscores, *Quality* refers to total quality score as defined in Appendix A along with other quality measurements; *IVOL* refers to idiosyncratic return volatility, as defined in Section 5.3.

Appendix C: Historical Development of Quality and Idiosyncratic Volatility

Figure C1

Historical Development of Aggregate Quality and Idiosyncratic Return Volatility

Panel A: Profitability and Idiosyncratic Return Volatility



Panel B: Growth and Idiosyncratic Return Volatility

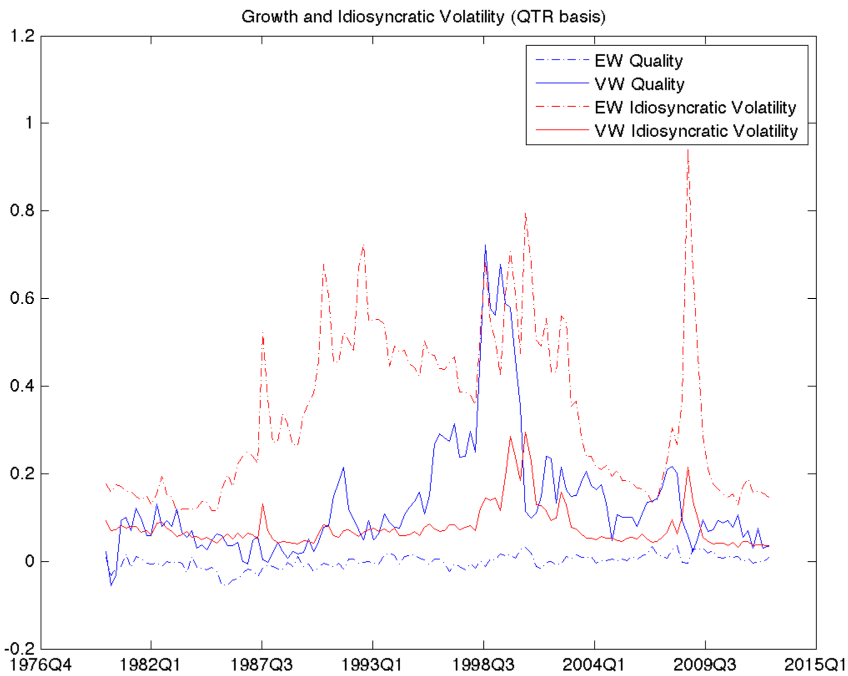
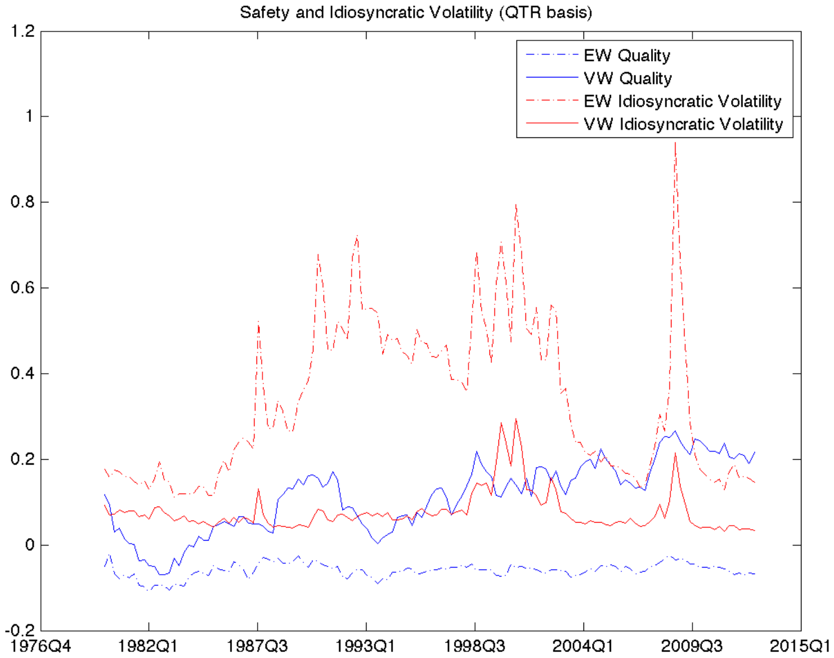


Figure C1 - continued

Historical Development of Aggregate Quality and Idiosyncratic Volatility

Panel C: Safety and Idiosyncratic Return Volatility



Panel D: Payout and Idiosyncratic Return Volatility

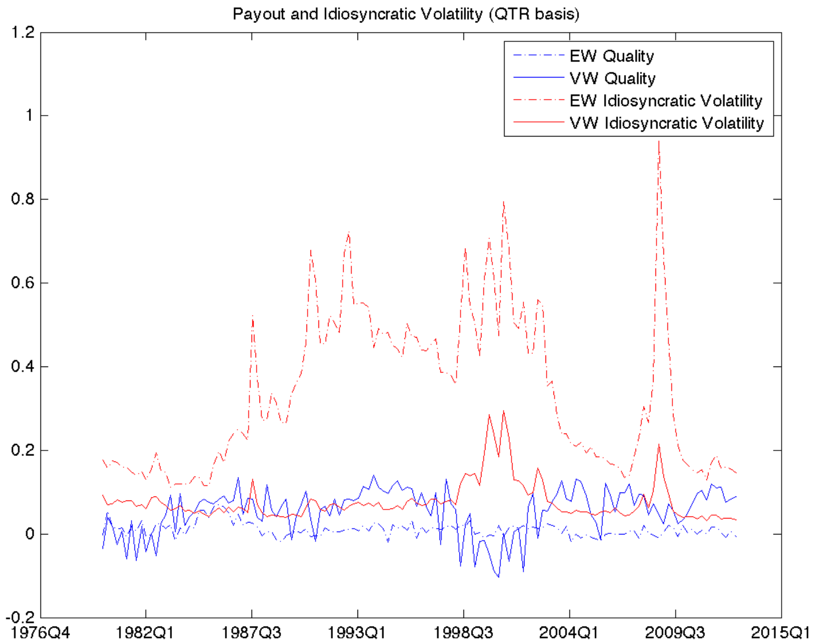
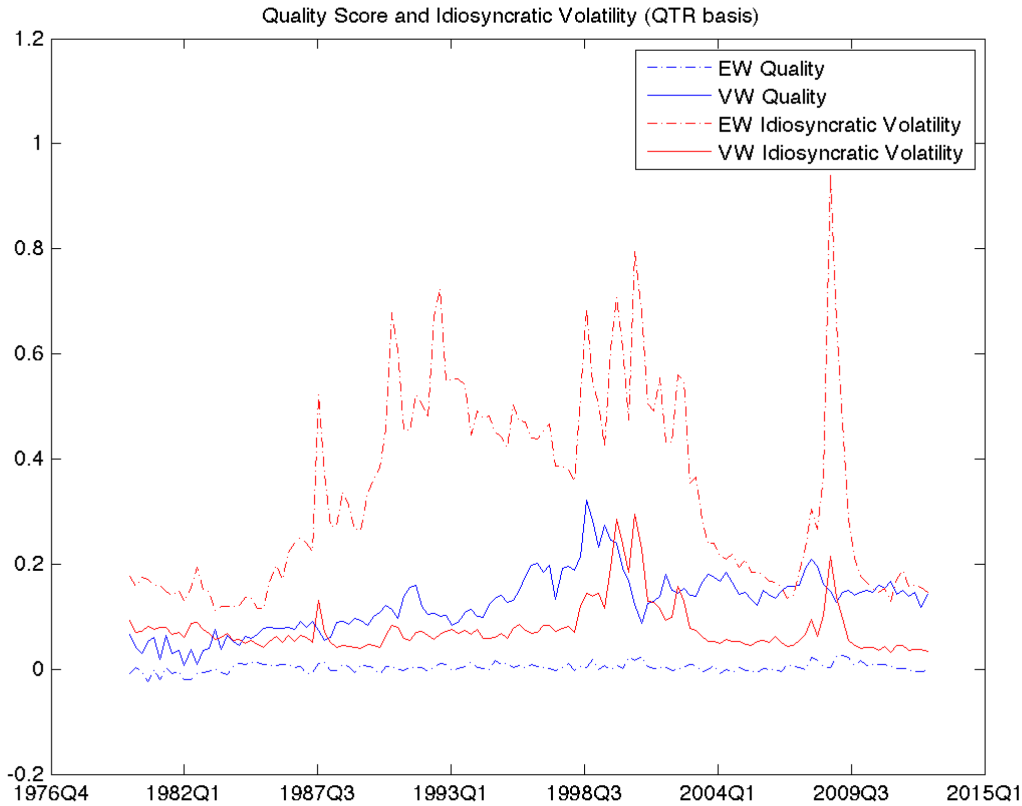


Figure C1 - continued
Historical Development of Aggregate Quality and Idiosyncratic Volatility

Panel F: Quality and Idiosyncratic Return Volatility



Note. In each panel *Quality* refers to respective dimension of quality score, as defined in Appendix A; *EW* and *VW* indicate average equally- and market-capitalization-weighed series. Market Capitalizations applied as weights are taken in a subsequent quarter to that for which the fundamental results are reported to address non-synchronicity in reporting.

Appendix D: Time-Series Properties

Table D1

Augmented Dickey-Fuller Tests on Aggregate Series

Panel A: Equally Weighted Indices

	Profitability	Growth	Safety	Payout	Quality	IVOL
p-val (simple)	0.60%	17.00%	0.00%	1.00%	0.58%	3.50%
p-val (drift)	0.02%	1.10%	0.00%	0.00%	0.02%	0.20%
p-val (trend)	3.70%	7.02%	0.01%	2.40%	3.7%	15.50%
Lags	4	4	1	2	4	1

Panel B: Value Weighted Indices

	Profit	Growth	Safety	Payout	Quality	Volatility
p-val (simple)	37.52%	6.60%	58.98%	17.15%	18.82%	6.90%
p-val (drift)	3.63%	0.30%	8.44%	1.20%	1.3%	0.36%
p-val (trend)	85.28%	26.58%	2.11%	43.06%	25.15%	23.49%
Lags	4	1	1	3	1	3

Note. *Profitability*, *Growth*, *Safety* and *Payout* refer to quality subscores, *Quality* refers to total quality score as defined in Appendix A; *IVOL* refers to idiosyncratic return volatility, as defined in Section 5.3. We test unit root against three alternatives - simple stationary process (*simple*), stationary process with a drift (*drift*) and time trend stationary process (*trend*). The number of lagged differences included in the test is determined by Bayesian information criterion. *Equally* and *Value-Weighted Indices* indicate average equally- and market-capitalization-weighed series. Market Capitalizations applied as weights are taken in a subsequent quarter to that for which the fundamental results are reported to address non-synchronicity in reporting.

Appendix E: Panel Stationarity Tests

Table E1
Panel Unit-root Tests

	$W_{\bar{t}}$	p-value	Lags
A. Return, Excess Return and Idiosyncratic Volatility			
Return	-72.00	0%	0.95
Excess Return	-191.45	0%	0.89
IVOL	-191.45	0%	0.89
B. Quality Scores			
Profitability	-106.57	0%	1.56
Growth	-102.49	0%	1.29
Safety	-41.44	0%	1.04
Payout	-180.45	0%	0.93
Quality	-120.08	0%	1.17
C. Profitability Measures			
GPOA	-41.91	0%	1.98
ROE	-98.04	0%	1.37
ROA	-86.92	0%	1.41
GMAR	-69.96	0%	1.33
ACC	-181.66	0%	1.61
D. Growth Measures			
ΔGPOA	-58.47	0%	1.49
ΔROE	-98.97	0%	1.14
ΔROA	-92.63	0%	1.09
ΔGMAR	-67.33	0%	1.36
ΔACC	-188.47	0%	1.39
E. Safety Measures			
LEV	-15.45	0%	1.19
EVOL	-5.20	0%	0.92
O-score	-90.63	0%	1.02
Z-score	-26.86	0%	1.55
BAB	-18.20	0%	1.72
F. Payout Measures			
DISS	-183.18	0%	1.03
EISS	-185.62	0%	0.74
NPOP	-29.82	0%	0.88

Note. *Return* refers to raw quarterly return series and *Excess Return* – to quarterly returns in excess of risk free rate. *IVOL* refers to idiosyncratic return volatility, as defined in Section 5.3. *Profitability*, *Growth*, *Safety* and *Payout* refer to quality subscores, *Quality* refers to total quality score as defined in Appendix A. Individual quality measurements are constructed as stated in Appendix A and are standardized. The test statistic, $W_{\bar{t}}$, is effectively the adjusted average of t-statistics over all firms obtained from traditional lag augmented Dickey-Fuller regression on the lagged independent variable; asymptotically it has normal distribution. All tests are performed on the demeaned data, as well as include time trend; if either the trend is excluded or the data is not demeaned, the results remain effectively unchanged. Number of lags is selected according to AIC with maximum allowed 4 lags to control for potential seasonality in the quarterly data.

Appendix F: Risk Adjusted Returns and Quality

Table F1

Panel Factor Model – Pricing Channels of Idiosyncratic Volatility and Profitability

Dependent Variable: Quarterly Excess Returns

		I	II	III
Const	coeff	-0.0002	0.0027	-0.0098
	SE	0.0030	0.0042	0.0031
	pval	95.4%	51.3%	0.2%
IVOL	coeff	0.0332		0.0420
	SE	0.0127		0.0131
	pval	0.9%		0.1%
GPOA	coeff		0.0173	0.0141
	SE		0.0030	0.0029
	pval		0%	0%
ROE	coeff		0.0033	0.0036
	SE		0.0027	0.0028
	pval		23.4%	20.0%
ROA	coeff		0.0253	0.0329
	SE		0.0047	0.0046
	pval		0%	0%
GMAR	coeff		-0.0079	-0.0076
	SE		0.0029	0.0031
	pval		0.7%	1.3%
ACC	coeff		-0.0041	-0.0044
	SE		0.0020	0.0019
	pval		3.7%	1.7%
	Adj. R^2	15.13%	14.57%	16.48%
	N	86,629	86,629	86,629

Note. The dependent variable is the quarterly return in excess of risk-free rate. Explanatory variables are – idiosyncratic return volatility, *IVOL*, as defined in Section 5.3, and standardized AFP (2013) *Profitability* measurements, as defined in Appendix A. Reported estimates are from a panel factor regression, with standard errors double-clustered by time and firm dimensions. *coeff* indicated the obtained point estimate, *SE* – standard error and *pval* – corresponding p-value. The table reports the effects of main variables on risk-adjusted return (alpha). To address non-synchronicity in reporting all market data (returns, factors and idiosyncratic volatility) are leading by one time period (quarter) relative to quality measurements.

Table F2

Panel Factor Model – Pricing Channels of Idiosyncratic Volatility and Growth

Dependent Variable: Quarterly Excess Returns

		I	II	III
Const	coeff	-0.0002	0.0074	-0.0025
	SE	0.0030	0.0042	0.0030
	pval	95.4%	7.6%	39.3%
IVOL	coeff	0.0332		0.0372
	SE	0.0127		0.0013
	pval	0.9%		0.4%
ΔGPOA	coeff		0.0024	0.0039
	SE		0.0021	0.0017
	pval		25.3%	2.5%
ΔROE	coeff		0.0045	0.0048
	SE		0.0018	0.0017
	pval		0.1%	0.5%
ΔROA	coeff		0.0255	0.0263
	SE		0.0031	0.0030
	pval		0%	0%
ΔGMAR	coeff		0.0011	-0.0002
	SE		0.0030	0.0028
	pval		69.8%	94.7%
ΔACC	coeff		0.0003	0.0003
	SE		0.0015	0.0015
	pval		85.1%	82.9%
	Adj. R^2	15.13%	14.19%	16.29%
	N	86,629	86,629	86,629

Note. The dependent variable is the quarterly return in excess of risk-free rate. Explanatory variables are – idiosyncratic return volatility, *IVOL*, as defined in Section 5.3, and standardized AFP (2013) *Growth* measurements, as defined in Appendix A. Reported estimates are from a panel factor regression, with standard errors double-clustered by time and firm dimensions. *coeff* indicated the obtained point estimate, *SE* – standard error and *pval* – corresponding p-value. The table reports the effects of main variables on risk-adjusted return (alpha). To address non-synchronicity in reporting all market data (returns, factors and idiosyncratic volatility) are leading by one time period (quarter) relative to quality measurements.

Table F3

Panel Factor Model – Pricing Channels of Idiosyncratic Volatility and Safety

Dependent Variable: Quarterly Excess Returns

		I	II	III
Const	coeff	-0.0002	0.0091	-0.0043
	SE	0.0030	0.0046	0.0032
	pval	95.4%	4.9%	18.3%
IVOL	coeff	0.0332		0.0405
	SE	0.0127		0.0133
	pval	0.9%		0.2%
LEV	coeff		0.0017	-0.0025
	SE		0.0021	0.0018
	pval		40.7%	16.3%
EVOL	coeff		0.0069	0.0056
	SE		0.0025	0.0024
	pval		0.7%	2.2%
Oscore	coeff		0.0168	0.0237
	SE		0.0031	0.0024
	pval		0%	0%
Zscore	coeff		-0.0120	-0.0059
	SE		0.0031	0.0027
	pval		0%	2.6%
BAB	coeff		0.0004	0.0015
	SE		0.0025	0.0025
	pval		88.2%	54.9%
	Adj.R^2	15.13%	15.97%	17.46%
	N	86,629	86,629	86,629

Note. The dependent variable is the quarterly return in excess of risk-free rate. Explanatory variables are – idiosyncratic return volatility, *IVOL*, as defined in Section 5.3, standardized AFP (2013) *Safety* measurements, as defined in Appendix A. Reported estimates are from a panel factor regression, with standard errors double-clustered by time and firm dimensions. *coeff* indicated the obtained point estimate, *SE* – standard error and *pval* – corresponding p-value. The table reports the effects of main variables on risk-adjusted return (alpha). To address non-synchronicity in reporting all market data (returns, factors and idiosyncratic volatility) are leading by one time period (quarter) relative to quality measurements.

Table F4

Panel Factor Model – Pricing Channels of Idiosyncratic Volatility and Payout

Dependent Variable: Quarterly Excess Returns

		I	II	III
Const	coeff	-0.0002	0.0085	-0.0004
	SE	0.0030	0.0043	0.0030
	pval	95.4%	4.8%	90.8%
IVOL	coeff	0.0332		0.0333
	SE	0.0127		0.0126
	pval	0.9%		0.8%
DISS	coeff		0.0051	0.0040
	SE		0.0013	0.0014
	pval		0%	0.4%
EISS	coeff		0.0019	0.0027
	SE		0.0014	0.0013
	pval		17.1%	3.2%
NPOP	coeff		-0.0010	0.0002
	SE		0.0025	0.0018
	pval		69.5%	90.7%
	adjR2	15.13%	13.23%	15.22%
	N	86,629	86,629	86,629

Note. The dependent variable is the quarterly return in excess of risk-free rate. Explanatory variables are – idiosyncratic return volatility, *IVOL*, as defined in Section 5.3, and standardized AFP (2013) *Payout* measurements, as defined in Appendix A. Reported estimates are from a panel factor regression, with standard errors double-clustered by time and firm dimensions. *coeff* indicated the obtained point estimate, *SE* – standard error and *pval* – corresponding p-value. The table reports the effects of main variables on risk-adjusted return (alpha). To address non-synchronicity in reporting all market data (returns, factors and idiosyncratic volatility) are leading by one time period (quarter) relative to quality measurements.

Table F5

Panel Factor Model – Pricing Channels of Idiosyncratic Volatility and Quality Measurements

Dependent Variable: Quarterly Excess Returns

	I			II			III		
	Coeff	**SE**	**pval**	**Coeff**	**SE**	**P-Value**	**Coeff**	**SE**	**pval**
Volatility									
IVOL	0.0332	0.0127	0.9%				0.0369	0.0130	0.4%
Profitability									
GPOA				0.0231	0.0035	0.00%	0.0191	0.0030	0.00%
ROE				0.0004	0.0028	87.4%	0.0007	0.0029	80.6%
ROA				0.0340	0.0047	0.00%	0.0347	0.0048	0.00%
GMAR				-0.0111	0.0029	0.00%	-0.0109	0.0029	0.00%
ACC				-0.0088	0.0021	0.00%	-0.0090	0.0020	0.00%
Growth									
ΔGPOA				0.0000	0.0022	99.7%	0.0013	0.0019	50.60%
ΔROE				0.0027	0.0017	9.90%	0.0030	0.0017	7.2%
ΔROA				0.0089	0.0032	0.50%	0.0347	0.0031	1.5%
ΔGMAR				0.0033	0.0025	19.3%	0.0036	0.0026	16.1%
ΔACC				0.0052	0.0013	0.00%	0.0055	0.0013	0.00%
Safety									
LEV				0.0057	0.0020	0.30%	0.0026	0.0018	15.5%
EVOL				0.0049	0.0023	3.40%	0.0042	0.0023	6.80%
Oscore				0.0013	0.0027	62.2%	0.0074	0.0020	0.00%
Zscore				-0.0345	0.0043	0.00%	-0.0230	0.0039	0.00%
BAB				-0.0026	0.0027	32.9%	0.0060	0.0026	1.90%
Payout									
DISS				0.0032	0.0013	1.10%	0.0024	0.0013	6.10%
EISS				0.0020	0.0012	10.3%	0.0022	0.0012	6.70%
NPOP				-0.0003	0.0025	90.3%	-0.0000	0.0022	99.7%
Const	-0.0002	0.0030	95.4%	0.0069	0.0043	10.8%	-0.0049	0.0032	13.0%
Adj. R2		15.13%			17.69%			18.96%	
N		86,629			86,629			86,629	

Note. The dependent variable is the quarterly return in excess of risk-free rate. Explanatory variables are – idiosyncratic return volatility, *IVOL*, as defined in Section 5.3, and all standardized AFP (2013) quality measurements, as defined in Section 5.2. Reported estimates are from a panel factor regression, with standard errors double-clustered by time and firm dimensions. *coeff* indicated the obtained point estimate, *SE* – standard error and *pval* – corresponding p-value. The table reports the effects of main variables on risk-adjusted return (alpha). To address non-synchronicity in reporting all market data (returns, factors and idiosyncratic volatility) are leading by one time period (quarter) relative to quality measurements.

Appendix G: Relation between Quality and Idiosyncratic Volatility

Table G1

Idiosyncratic Risk and Profitability & Growth Measurements

Dependent Variable: Idiosyncratic Return Volatility

Panel A: Profitability			Panel B: Growth		
Const	coeff	0.3083	Const	coeff	0.2796
	SE	0.0165		SE	0.0151
	pval	0%		pval	0%
GPOA	coeff	0.0763	ΔGPOA	coeff	-0.0056
	SE	0.0094		SE	0.0066
	pval	0%		pval	39%
ROE	coeff	-0.0025	ΔROE	coeff	-0.0137
	SE	0.0068		SE	0.0037
	pval	71%		pval	0%
ROA	coeff	-0.2013	ΔROA	coeff	-0.0378
	SE	0.0167		SE	0.0074
	pval	0%		pval	0%
GMAR	coeff	-0.0050	ΔGMAR	coeff	-0.0293
	SE	0.0099		SE	0.0104
	pval	62%		pval	1%
ACC	coeff	0.0046	ΔACC	coeff	-0.0004
	SE	0.0030		SE	0.0021
	pval	12%		pval	86%
	Adj.R^2	6.09%		Adj.R^2	0.74%
	N	88,378		N	88,378

Note. The dependent variable is the idiosyncratic return volatility, *IVOL*, as defined in Section 5.3; explanatory variables are standardized AFP (2013) *Profitability* (Panel A) and *Growth* (Panel B) measurements, as defined in Appendix A. Reported estimates are from a panel factor regression, with standard errors double-clustered by time and firm dimensions. *coeff* indicated the obtained point estimate, *SE* – standard error and *pval* – corresponding p-value. To address non-synchronicity in reporting all market data (returns, factors and idiosyncratic volatility) are leading by one time period (quarter) relative to quality measurements.

Table G2

Idiosyncratic Risk and Safety & Payout Measurements

Dependent Variable: Idiosyncratic Return Volatility

Panel A: Safety			Panel B: Payout		
Const	coeff	0.3421	Const	coeff	0.2773
	SE	0.0188		SE	0.0149
	pval	0%		pval	0%
LEV	coeff	0.1139	DISS	coeff	0.0178
	SE	0.0117		SE	0.0027
	pval	0%		pval	0%
EVOL	coeff	0.0360	EISS	coeff	-0.0255
	SE	0.0087		SE	0.0037
	pval	0%		pval	0%
Oscore	coeff	-0.1881	NPOP	coeff	-0.0540
	SE	0.0135		SE	0.0111
	pval	0%		pval	0%
Zscore	coeff	-0.1284			
	SE	0.0159			
	pval	0%			
BAB	coeff	-0.0354			
	SE	0.0088			
	pval	0%			
	Adj.R^2	12.18%		Adj.R^2	0.73%
	N	88,378		N	88,378

Note. The dependent variable is the idiosyncratic return volatility, *IVOL*, as defined in Section 5.3; explanatory variables are standardized AFP (2013) *Safety* (Panel A) and *Payout* (Panel B) measurements, as defined in Appendix A. Reported estimates are from a panel factor regression, with standard errors double-clustered by time and firm dimensions. *coeff* indicated the obtained point estimate, *SE* – standard error and *pval* – corresponding p-value. To address non-synchronicity in reporting all market data (returns, factors and idiosyncratic volatility) are leading by one time period (quarter) relative to quality measurements.

Table G3

Pooled Regression

Dependent Variable: Idiosyncratic Return Volatility	Coeff	SE	pval
Profitability			
GPOA	0.1056	0.0107	0%
ROE	-0.0053	0.0060	38%
ROA	-0.0472	0.0170	1%
GMAR	-0.0087	0.0107	42%
ACC	0.0027	0.0039	48%
Growth			
ΔGPOA	-0.0299	0.0069	0%
ΔROE	-0.0071	0.0035	4%
ΔROA	0.0360	0.0089	0%
ΔGMAR	-0.0132	0.0057	2%
ΔACC	-0.0041	0.0030	17%
Safety			
LEV	0.0876	0.0115	0%
EVOL	0.0217	0.0082	1%
Oscore	-0.1717	0.0125	0%
Zscore	-0.1504	0.0190	0%
BAB	-0.0343	0.0085	0%
Payout			
DISS	0.0121	0.0023	0%
EISS	-0.0061	0.0027	2%
NPOP	-0.0206	0.0089	2%
Const	0.3346	0.0183	0%
Adj. R^2		14.38%	
N		88,378	

Note. The dependent variable is the idiosyncratic return volatility, *IVOL*, as defined in Section 5.3; explanatory variables are all standardized AFP (2013) quality measurements, as defined in Appendix A. Reported estimates are from a panel factor regression, with standard errors double-clustered by time and firm dimensions. *coeff* indicated the obtained point estimate, *SE* – standard error and *pval* – corresponding p-value. To address non-synchronicity in reporting all market data (returns, factors and idiosyncratic volatility) are leading by one time period (quarter) relative to quality measurements.

Appendix H: Correlation Structure

Table H1

Correlation Structure: Quality Measurements and Idiosyncratic Return Volatility

	IVOL	GPOA	ROE	ROA	GMAR	ACC	ΔGPOA	ΔROE	ΔROA	ΔGMAR	ΔACC	LEV	EVOL	O-Score	Z-Score	BAB	DISS	EISS	NPOP
IVOL	1.00																		
GPOA	0.04	1.00																	
ROE	-0.13	0.17	1.00																
ROA	-0.22	0.32	0.55	1.00															
GMAR	-0.04	0.37	0.18	0.32	1.00														
ACC	0.05	-0.04	-0.10	-0.18	-0.02	1.00													
ΔGPOA	-0.04	0.38	0.12	0.21	0.21	-0.06	1.00												
ΔROE	-0.07	0.16	0.28	0.43	0.15	-0.09	0.28	1.00											
ΔROA	-0.08	0.24	0.38	0.61	0.23	-0.12	0.44	0.67	1.00										
ΔGMAR	-0.01	0.11	0.06	0.07	0.23	-0.02	0.61	0.21	0.32	1.00									
ΔACC	0.01	-0.04	-0.07	-0.10	-0.01	0.66	0.03	-0.11	-0.15	0.05	1.00								
LEV	-0.06	0.24	0.05	0.16	0.01	-0.01	0.07	0.09	0.12	-0.04	-0.01	1.00							
EVOL	0.12	-0.01	-0.04	-0.19	-0.04	0.03	0.01	-0.04	-0.03	0.07	0.01	-0.24	1.00						
O-Score	-0.27	0.20	0.28	0.48	0.13	-0.08	0.13	0.22	0.30	0.00	-0.04	0.59	-0.22	1.00					
Z-Score	-0.24	0.40	0.23	0.51	0.18	-0.09	0.20	0.12	0.17	-0.03	-0.03	0.36	-0.24	0.44	1.00				
BAB	-0.05	-0.03	0.06	0.09	0.04	-0.01	-0.11	0.03	0.03	-0.09	-0.04	-0.04	-0.09	-0.06	-0.01	1.00			
DISS	0.03	0.06	0.02	0.03	0.00	0.22	-0.03	0.02	0.03	-0.02	0.14	0.11	0.01	0.07	0.00	0.00	1.00		
EISS	-0.05	0.07	0.06	0.10	0.05	0.00	-0.06	0.00	0.01	-0.08	-0.01	0.04	-0.07	0.08	0.14	0.03	-0.01	1.00	
NPOP	-0.07	-0.02	0.04	0.10	-0.13	-0.01	-0.13	0.01	-0.01	-0.15	-0.04	0.00	-0.07	0.07	0.09	0.04	0.01	0.09	1.00

Note. *IVOL* refers to the idiosyncratic return volatility, as defined in Section 5.3; all other variables are standardized AFP (2013) quality measurements, as defined in Appendix A.

Table H2

Correlation Structure: Quality (Sub)scores and Volatility

	IVOL	Profitability	Growth	Safety	Payout	Quality
IVOL	1.00					
Profitability	-0.10	1.00				
Growth	-0.06	0.46	1.00			
Safety	-0.20	0.36	0.14	1.00		
Payout	-0.04	0.15	-0.04	0.12	1.00	
Quality	-0.16	0.76	0.65	0.61	0.50	1.00

Note. *IVOL* refers to the idiosyncratic return volatility, as defined in Section 5.3; *Profitability*, *Growth*, *Safety* & *Payout* refer to quality subscores and *Quality* – to total quality score, as defined in Appendix A.