CREDIT CYCLES AND ASSET PRICE BUBBLES

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ABSTRACT

By analyzing 43 economies over 1870-2016, we find evidence that large credit expansions interacted with rapid price run-ups, have strong forecasting power for negative future returns. The mean cumulative excess return is -22.1% for the housing market over 6 years, and -15.4% for the stock market over 3 years. Growth stocks, stocks with high levels of analyst disagreement, and highly leveraged stocks are particularly vulnerable to the bust, with their respective factor portfolios significantly underperforming compared to their unconditional means. We show that by avoiding stocks with extreme exposures to the credit cycle, investors can partially mitigate the risks induced by a credit-fueled bubble.

JEL Codes: G01, G02, G15, G21

Key Words: International Finance, Banks, Financial Crises

Current Version: Nov 9, 2021

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* We gratefully acknowledge helpful comments from Nikolai Boboshko, Julieta Caunedo, Andrew Karolyi, Raul Morales, Kristoffer Nimark, Eswar Prasad, Mathieu Taschereau-Dumouchel as well as seminar participants at Cornell University. All remaining errors are of course the responsibility of the authors alone.

I. INTRODUCTION

The global financial crisis renewed interest amongst economists, practitioners and regulators on understanding the consequences of credit booms. A growing body of evidence shows that large credit expansions can have severe negative impacts on the real economy, leading to banking crises, housing market crashes and economic recessions (Borio and Lowe 2002, Mian and Sufi 2009, Schularick and Taylor 2012, López-Salido, Stein, and Zakrajšek 2016, Baron and Xiong 2017, and Baron, Verner and Xiong 2018). However, despite the well-cited views of Minsky (1977) and Kindleberger (1978) that financial crises are "credit booms gone wrong", the dynamics of credit booms and asset returns are far from clear.

Earlier work in the macroeconomics literature documenting the destabilizing effects of credit booms on financial markets were centered on a small number of events in emerging markets associated with currency instability or sovereign debt problems (McKinnon and Pill 1997, Kaminsky and Reinhart 1999, and Gourinchas, Valdes, and Landerretche 2001). Schularick and Taylor (2012) made significant contributions to the discussion by constructing a novel long-run historical dataset for 14 developed countries and showed that changes in bank credit are a robust predictor of financial crises. However, while financial markets were the setting for these papers, the common focus were still distinctively on real outcomes, rather than asset returns.

The finance field, on the other hand, has recognized the importance of the balance sheet quantities of financial intermediaries in asset pricing. This gradually led to the development of the influential intermediary asset pricing literature. (Shleifer and Vishney 1997, Xiong 2001, Kyle and Xiong 2001, Gromb and Vayanos 2002, Brunnermeier and Pedersen 2009, He and Krishnamurthy 2012, 2013, Adrian, Monech and Shin 2013, Adria, Etula and Muir 2013, Brunnermeier and Sannikov 2014, and Baron and Muir 2018). Research shows that intermediary asset pricing is

likely more consequential in normal times, rather than extreme times when credit is on a rapid upwards trajectory.

Our objective is to directly examine the predictive power of credit expansions on future asset returns. In doing so, we bring together the macroeconomic literature which utilizes credit expansion and finance literature which studies asset returns. The current gap in the literature does not reflect a lack of interest, but rather the limited availability of credit data to conduct robust empirical tests, further exacerbated by the fact that credit booms are by definition rare events.

To address this issue, we utilize a newly constructed panel data set for 24 developed economies and 19 emerging economies that spans from 1870 – 2016. As in Baron and Xiong (2017), we use bank credit expansion, the past three-year change in the bank credit to GDP ratio in each country, as a proxy for total credit expansion. Bank credit is the amount of net new lending extended by the banking sector to domestic households and nonfinancial corporations. While Baron and Xiong (2017) and Baron, Verner and Xiong (2018) utilize the same explanatory variable, their outcome variable is limited to banking sector returns. In contrast, we focus on the entire stock market and the housing market, this allows us to quantify the impact that credit booms have on a much broader class of investors.

Our analysis focuses on three questions from the perspective of investors. First, is credit expansion a reliable predictor for housing market and stock market bubbles? We characterize price bubbles as events in which future market returns are negative, and while our criteria are somewhat arbitrary, we select it for its simplicity and as it is not explainable by elevated risk appetite. Similar to Greenwood, Shleifer and You (2019), we find that "Fama is mostly right". Alone, rapid credit expansion predicts lower returns for both housing markets and stock markets, but it precedes significant negative returns only for the housing market, not for the stock market. However, when

interacted with other indicators, large credit booms predict negative returns in both housing and stock markets that are statistically significant and economically large. In particular, price run-ups that occur during credit booms are dangerous signals. The mean cumulative excess returns in housing markets in subsequent four, five and six years is substantially negative at -18.7% (with a *t*-statistic of -1.88), -21.8% (with a *t*-statistic of -1.90) and -22.1% (with a *t*-statistic of -1.83). Meanwhile, the mean cumulative excess returns in stock markets in the subsequent one, two and three years is -2.0% (with a *t*-statistic of -0.52), -11.8% (with a *t*-statistic of -1.89) and -15.4% (with a *t*-statistic of -2.36).

Our results provide formal statistical evidence for the views of Minsky (1977) and Kindleberger (1978). They can be further interpretated under the theoretical framework of Simsek (2013). Building on earlier work by Geanakoplos (2003, 2010), Simsek develops a tractable model in which credit booms arise only in states where creditors and borrowers have similar beliefs on downside risk. The credit boom eases the financial constraints of optimistic borrowers, amplifying their impact on asset prices, causing a subsequent asset market boom and bust.

Given that a stock market run-up during credit booms is a strong signal for a bubble, our second question asks whether the conditional excess returns of individuals stocks in subsequent years are related to their characteristics. We define a stock market run-up that coincides with a credit boom as a credit-fueled stock market boom. To answer this question, we turn to factor high-minus low (HML) portfolios commonly used in the finance literature. Using individual stock return data for 20 developed economies from 1980-2016, we find that stock characteristics have strong explanatory power for explaining the cross section of excess returns following a credit-fueled stock market boom. There is little evidence for over-extrapolation, as the conditional returns on the

momentum portfolio and sales growth HML portfolio do not significantly deviate from their unconditional mean following a credit-fueled boom.

Valuation matters strongly, with the Book to Market, Earnings to Price and Dividend Yield HML portfolios outperforming their unconditional returns by 5.2% (not significant), 28.0% (significant at 1% level) and 17.9% (significant at 10% level) over a three-year window. Stocks with higher levels of analyst disagreement and younger firms also perform relatively poorer following a credit-fueled stock market boom (-24.1% with *t*-statistic of -2.28 and -10.7% with *t*-statistic of -3.38, respectively). Taken together, our results suggest that stocks with a wider disparity in returns are particularly sensitive to the boom and bust cycle of a credit-fueled stock market boom. Optimistic borrowers, enticed by the upside potential of young growth stocks, leverage loose credit conditions and disproportionately bid up their prices.

There is also a clear economic channel through which credit booms impact stock returns. The credit crunch that follows the credit boom limits the ability of *all* firms to roll-over long term debt and negatively impacts their ability to invest in profitable projects. However, highly leveraged firms rely more on external financing and are particularly sensitive to credit conditions. Highly leveraged firms underperform unconditionally, with their returns over a two to three year horizon to be around 1.5% lower annually (significant at the 1% level) compared to their counterparts with low leverage. The conditional underperformance is far more drastic. In the next one, two and three years following a credit fueled boom, the average returns on the leverage HML portfolio is 7.1%, 14.0% and 17.0% lower than its unconditional mean, and the difference is highly statistically significant. As our analysis is conducted only with information that the investor could observe at a point in time, it also has important implications for factor timing.

Our last question concerns whether an investor can form strategies to avoid the downside risk associated with a credit-fueled stock market boom. We start our investigation by constructing a credit-beta HML portfolio based on a stock's return sensitivity to credit expansion. Our results suggest that stocks which have extreme exposures to the credit cycle, whether positive or negative, tend to underperform their peers with more moderate exposures.

II. DATA

We construct a panel data set for 24 developed economies and 19 emerging economies with annual observations from 1870 – 2016. The two world war periods from 1914 – 1918, and 1939 – 1945 are omitted from our sample. Our definition of a developed/emerging market is based on classification from MSCI.[1] However, it should be noted that due to the historical nature of our dataset, the classification does not necessarily always match stages of development for an economy at a given point in time.

II.A. Data Construction

The data set primarily consists of three types of variables: credit expansion, market index returns and characteristics, and individual stock data. The construction of the data is outlined below.

1. Credit Expansion. As in Baron and Xiong (2017), our key explanatory variable *credit expansion* is defined as the annualized past three-year percentage point change in bank credit to GDP. Bank credit is measured as credit extended by the banking sector to domestic households

[1] https://www.msci.com/developed-markets

and nonfinancial corporations. Throughout this paper, credit expansion refers to bank credit expansion except where specifically noted. Mathematically, *credit expansion* is expressed as:

$$\Delta\left(\frac{bank\ credit}{GDP}\right)_t = \frac{\left(\frac{bank\ credit}{GDP}\right)_t - \left(\frac{bank\ credit}{GDP}\right)_{t-3}}{3}$$

To construct our credit expansion measure, we combine data from the Bank of International Settlements (BIS) and Schularick and Taylor (2012) in the same fashion as Baron and Xiong (2017). The BIS data is "bank credit" under "long series on credit to private non-financial sectors". The BIS data set covers all 43 economies in our sample but is generally available only after the second world war. "Bank loans" from the Schularick and Taylor dataset extends back for more than a century to 1870 but is only available for 14 developed countries. While both data sets define banks broadly and exclude interbank lending and lending to governments and government-related entities, there are discrepancies between how the two sources define banks and credit. Most notably, while "bank credit" from the BIS data set includes loans, leases and securities from banks to domestic households and private nonfinancial corporations, "bank loans" in Schularick and Taylor (2012) is more narrowly defined as loans and leases to domestic households and private nonfinancial corporations.

Whenever there is an overlap between the series, we used the BIS data to stay consistent with Baron and Xiong (2017). We keep in mind the potential discrepancies between the two series and take care to avoid breaks in our merged *credit expansion* variable. The Schularick-Taylor data is scaled for each country by an affine function so that the overlap between the series joins without a break and has similar variance for the overlap.

We use *credit expansion* rather than credit level to control for large credit changes that may coincide with large increases in GDP. Given that various countries experience various averages and different volatilities of *credit expansion*, we standardize *credit expansion* for each country. To

avoid look-ahead bias, we standardize using only past data. For example, to standardize US *credit expansion* in 1970, we calculate the mean and standard deviation of *credit expansion* for the US from 1870 – 1969 and use these values to standardize the given observation. This allows us to draw inferences with data that would also be observable for regulators and investors in real time.

The effects that credit expansion have on asset prices might be driven by extreme events rather than linear. We generate a *credit boom* indicator to capture these effects. The *credit boom* indicator takes the value of 1 if *credit expansion* exceeds the 90th historical distribution, and 0 otherwise.

2. Market Index Returns and Characteristics. Our second set of data consists of stock and housing market index returns along with market characteristics that have been shown in the literature to predict market returns.

We calculate stock market returns as log excess total returns:

$$log\ excess\ total\ returns_t = log(\frac{stock\ market\ index_t}{stock\ market\ index_{t-1}} + div\ yield_t - r_t^{3M})$$

We start with price data for stock market indexes by combining data from Global Financial Data for 1920 – 1980 with that from Datastream for 1981 – 2016. Average dividend yield is collected from Datastream and supplemented with data from Compustat, stock exchange websites and central bank statistics. The three-month short-term interest rate for each sample country r_t^{3M} is collected from Global Financial Data.[2]

We measure housing market returns in log excess price returns:

$$log\ excess\ price\ returns_t = log(\frac{housing\ market\ index_t}{housing\ market\ index_{t-1}} - r_t^{3M})$$

[2] We use the individual country level three-month short-term interest rate rather than the three-month US treasuries rate to account for levels of high inflation in Argentina etc.

Price data for housing market is from Jorda et al. (2019).

Stock market characteristics include average dividend yield, aggregate stock volatility, P/E ratio, B/M ratio, turnover and cumulative excess returns for the past three years. Housing market characteristics include rental yields and cumulative excess returns for the past six years. We use cumulative excess returns for both markets. The remaining stock market characteristics are from Global Financial Data from 1920 – 1980 and Datastream from 1981 – 2016. Rental yields are from Jorda et al. (2019).

Table 1 presents summary statistics for market returns, characteristics and credit expansion.

3. Individual Stock data. The last portion of our data set consists of international stock returns and characteristics from Datastream International and company account items from Worldscope. Datastream International, alongside Compustat Global, is one of the two major sources of data for research involving international stocks and has been used by many researchers for its broad and deep coverage.[3]

We begin by downloading end-of-month stock prices, market capitalization, return indexes, dividend yield and stock split information from Datastream from July 1981 to December 2019. We identify securities trading on a country's exchange through Datastream's constituent lists. For the United States, we use FAMERA-FAMERZ (where each letter of the alphabet represents a list) for securities currently trading on U.S. exchanges and DEADUS1–DEADUS12 for securities that are no longer traded. For Non-U.S. countries, we use WSCOPE followed by the two-digit Datastream country code (e.g. WSCOPEAU for Australia), which identifies all active and inactive securities domiciled within the economy. We exclude management investment offices, unit

[3] Griffin (2002), Griffin, Ji, and Martin (2003), Doidge (2004), Naranjo and Porter (2005), Kaniel, Li, and Starks (2005), Bekaert, Harvey, and Lundblad (2006), Hou, Karolyi, and Kho (2011) and Karolyi and Wu (2018) are examples of influential papers that utilize Datastream International.

investment trusts, real estate investment trusts and investors not classified (SIC code 6722, 6726, 6798, 6799) from our sample. Stocks must have at least 12 monthly stock returns during our sample period to be included. We combine the aforementioned monthly variables with annual information from Datastream International (market beta, volatility, turnover), I/B/E/S (analyst forecasts) and Worldscope (company account).

We address several preliminary issues with the Datastream International data set. First, it contains entries for individual issues of securities alongside the main company records. We keep only the main company records by screening on the last digit of the Worldscope permanent identifier (WC06105). Specifically, entries for which the last digit is "0" (company identifier) are retained and entries for which the last digit is an alphabetic letter (security identifier) are dropped. For companies with multiple issues, Worldscope selects the share that is available for foreign investment and most widely traded for the main company record.[4] Next, for most countries we keep only domestic firms listed on the nation's primary exchange. However, multiple exchanges are included for China (Shanghai and Shenzhen exchanges), Japan (Osaka and Tokyo exchanges) and the United States (NYSE, AMEX, and NASDAQ). Specifically, we apply a filter based on Stock Exchange(s) Listed (Worldscope Field 05427). This procedure screens out firms that are only listed on foreign exchanges, minor domestic exchanges, traded over the counter (OTC) or non-traded. After these three procedures, we have 25,398 firms and 649,598 firm-month observations.

Several types of data entry errors exist in Datastream International. We follow Ince and Porter (2006) in applying several additional filters to mitigate their impact on our analysis. First, for delisted firms, Datastream repeats the last valid data point until the end of our sample period. To

[4] This implies that the share price on the main company record reflects that of the primary security issue, other variables such as shares outstanding, market value, book value are consolidated at the company level.

eliminate these dummy records, we drop all monthly observations from the end of the sample period to the first non-zero return. Second, Datastream rounds stock prices and the total return index to the nearest 0.01. To avoid miscalculating returns due to the discreteness of the data, we drop observations for which the end-of-previous-month stock price falls below the 5% level within the country-month distribution.[5] This measure has the additional benefit of minimizing the influence of bid-ask bounces for low priced and/or illiquid stocks. In the absence of capital actions, we calculate monthly returns using price percentage changes in the stock price.[6] When there is a capital action, we calculate monthly returns as the percentage change in the total return index. Third, Datastream contains recording errors for stock prices which can lead to implausible returns. We screen for this by setting to missing any return above 300% that is reversed within one month. Specifically, if $R_t > 300\%$ or $R_{t-1} > 300\%$, and $(1 + R_{t-1}) * (1 + R_t) - 1 < 50\%$, then we set both R_{t-1} and R_t to missing. Furthermore, we treat as missing the monthly returns that fall outside the 0.1% and 99.9% percentile ranges in each country.

We construct our high-minus-low (HML) portfolios from the cleaned data set. To ensure that stocks are sorted into portfolios based on observable data in real time, we follow Fama and French (1992) and match financial statement data for fiscal year-end in year $t - 1$ with monthly returns from December of year t to November of year $t + 1$. We deviate slightly from the norm of formulating portfolios at the end of July because this allows us to match with the formulation procedure of Fama and French for their individual country portfolios.[7] Our book-to-market (B/M), dividend yield (D/P), earnings-to-price (E/P) portfolios are computed using a firm's market

[5] Another common filter is dropping observations for which the stock price falls below 1 U.S. Dollar.
[6] When there is a capital action (dividend payout, stock split, repos etc.), it is reflected in a change in the accumulated adjustment factor (AF).
[7] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library/int_country_port_formed.html

capitalization reported by Datastream at the end of December of year t.[8] Book equity is book equity per share (WC05476) multiplied by number of shares outstanding at fiscal year-end (WC05301). Dividend payout is dividend per share (WC05101) multiplied by number of shares outstanding. Total earnings are earnings per share (WC05201) multiplied by number of shares outstanding. Net sales growth (WC08698) is year-on-year net sales/revenue growth. Size is defined as the market equity at the end of December in year t. Firm age is the time since a firm's establishment (WC18272) or incorporation (WC18273). Leverage (WC08231) is long term debt (WC03251) divided by common equity (WC03501). Equity issuance is net proceeds from Sale/Issue of common and preferred stock (WC04251) in year $t-1$ divided by market capitalization in December of year $t-2$. Stock volatility (400E) is the standard deviation of end-of-week stock prices divided by their mean from January to December of year t. Market Betas (897E) are estimated annually for each stock at the end of December each year, using its previous 60 monthly returns, with a minimum of 30 monthly returns. Analyst dispersion measures disagreement in analyst earnings per share forecasts for the next financial year. It is the standard deviation of all analyst earnings per share forecasts (EPS1MN) for a company divided by their mean (EPS1SD). Momentum for month $q+1$ is the cumulative return from month $q-11$ to month $q-1$, we skip the return of month q to mitigate bid-ask bounces, short term reversals or nonsynchronous trading.

The accuracy of the inferences we draw from our HML portfolios rely on generating accurate returns on these portfolios. We compare our returns against two measures for external validation.

[8] Datastream adjusts for changes in shares outstanding at a monthly frequency. Thus, we use this measure and do not calculate market capitalization using end of December share prices multiplied by shares outstanding at fiscal year end (WS item5301) due to many countries having fiscal year ends that are not in December. The latter method can lead to potential mismatches when a firm experiences a change in shares outstanding between December and the fiscal year end.

We apply a preliminary check by comparing our value weighted average returns for each market with that obtained by Fama and French, and with the market index returns we collected in sub-section II.A.2. Furthermore, we benchmark our market level book-to-market, earnings-to-price and dividend-to-price HML portfolios against those reported by Fama and French, and our momentum portfolios against those reported by AQR Capital Management. We present summary statistics of individual stocks in Table 2.

III.EMPIRICAL RESULTS

III.A. Market Index Returns

Table 3 presents our baseline estimates on the impact that credit expansions have on the excess returns in stock and housing markets. In Panel A, the dependent variable is the excess housing market return over multiple time horizons. In columns (1) and (2), we see that the short-run (one year) impact of a normalized credit expansion or a large credit boom is essentially zero and insignificant. Over time though, the estimated coefficients grow in size and become negative. For example, four years after a normalized credit expansion or a large credit boom, the coefficients on the two variables are -0.015 and -0.081, respectively. This means that a one standard deviation increase in our normalized credit expansion measure decreases cumulative excess returns over four years by 1.5%, while a large credit boom lowers returns by 8.1%. At the longest time horizon that we observe in our paper, six years, the estimated impact from a normalized credit expansion is a decrease in cumulative returns by 2.6% and an incidence of a large credit boom by 12.8%. These results are highly significant, we are confident of them at the one percent significance level.

Given that credit expansions lower excess housing market returns, it is then reasonable to ask how important an expansion is in relation to the overall trends. Specifically, is the negative effect of a long-run credit expansion detrimental enough to turn total market returns negative? We

calculate total returns by adding the coefficient on the average market returns over a given time horizon (the constant) and our coefficients of credit expansion. The broad pattern of the results follows our measures of credit expansions. Initial estimates over one year are zero but are increasingly negative over time. Unfortunately, they are noisy, and we lack the power to precisely identify them. Total returns are significant at the ten percent level at the five and six year time horizon. A large credit boom predicts total returns to be on average -10.4% after five years and -12.2% after six years.

In Table 3, Panel B we measure the impact of our credit expansion measures on excess returns in the stock market. In contrast to the housing market results, the negative impact of a credit expansion is immediate. Over a one year time horizon, a one standard deviation in our normalized credit expansion measure lowers excess returns by 2.5% and it is highly statistically significant. Furthermore, the short-run impact of a large credit boom is also immediate and negative. One year out, excess returns decline by 7%. After three years, the negative impact of our normalized measure and a large credit boom are declines of cumulative excess returns by 5.5% and 13.7%, respectively.

Even though credit expansions tend to lower excess returns, the total returns during a credit boom are inconsistent. Estimates vary over different time horizons and credit expansion measures.

In Table 4, we present a two-way cross tabulation of credit booms and events when market characteristics are very high or low. It is clear that large credit booms are more likely associated with periods of high valuation (low rent yield, low dividend yield, high PE ratio, low book to market ratio), more trading activity (high turnover) and a price run-up (high past returns).

In Table 5 we specially explore the relationship between periods of credit expansion and past market performance. We augment our baseline specification by including a measure of high past excess returns that is also interacted with the credit boom variable. Results for the housing market

are presented in Panel A. As expected, returns are highly serially correlated as high past returns are correlated with high future returns. The coefficient on the high past returns variable is positive and significant over every time horizon. In the short-run, column (1), high past returns increase one-year cumulative excess returns by 0.039 and the estimate is significant at the one percent level. Over six years, column (11), the coefficient on high past returns is 0.044 and is significant at the ten percent level. We expect noisier estimates over longer time horizons as the serial correlation in excess returns is weaker in the long-run than in the short-run. More shocks hit the economy over longer horizons that break the serial correlation.

It is encouraging that the high past returns variable behaves as expected. Including it also does not change our conclusions about the impact of credit expansions. The coefficient on large credit booms is negative, increases in size over time, and achieves statistical significance in the long run. The key new variable that we are interested in is the interaction between large credit expansions and high past returns. Our hypothesis is that this interaction term should be highly negative and significant. Indeed, that is the case. Only over the one-year time horizon, where the coefficient on the interaction term is -0.021, is it small and not-significant. Over all the other time horizons, periods of high past returns and a large credit expansion significantly lowers future excess returns. After two years, these periods lower returns by 8.1%, the estimates grow until it reaches a height of -22.5% at the five-year time horizon. After six years, it shrinks, but only marginally, to -21.0%.

Turning our attention to total returns, these periods of credit expansion and high past returns lead to negative total returns over long-time horizons. Results for horizons of three or less are not significant, and the one-year horizon total returns is positive. At four years though, the estimated total returns are consistently large, negative and significant at the ten percent level. Estimates range from -18.7% (after four years) to -22.1% (after six years).

In Panel B, we test the interaction between rental yields and periods of credit expansion. Specifically, we test the interaction between periods of low rental yields and credit booms. As expected, the coefficient on low rental yield is negative in every specification. For example, over three years, a period of low rental yields decreases excess housing returns by 3%. Estimates increase over time, such that after six years excess housing returns fall by 6.9%.

The interaction between the large credit boom and the low yield variables is not-statistically significant in any specification. The coefficients are small and negative over short time horizons but become positive over longer periods. The largest estimate we observe is that after six years the coefficient rises to 0.069. Given the estimate on the interaction term, it is not surprising that the estimates on total returns are not significant. Even so, the estimates are large. Over six years, average cumulative excess returns are -16%.

In Table 6 we explore how features of the stock market interact with periods of credit expansion. Specifically, we look at periods of high past excess returns, low dividend yields, high daily stock volatility, low daily stock volatility, high price-to-earnings ratios, low book-to-market ratios, and high turnover interact with credit expansions. Apart from high past excess returns and low-dividend yields, none of these measures matter. To briefly summarize the results, we focus the discussion on column (6) and on the total returns. The addition of high past excess returns to our model predicts average future total returns of -15.4% over three years and the estimate is significant at the one percent confidence level. This further reinforces the evidence from the housing market that a credit-fueled stock market boom is a dangerous signal for future returns. In periods of low dividend yields, the average future return is -13.6% over three years and is also significant at the one percent level. For none of the other measures are total returns statistically

different from zero. The estimates range from an increase in total returns of 11.1% (stock volatility) to a decline of -10% (low book-to-market).

In table 7, we show that the probability of a housing market crash or stock market crash conditional on observing a credit boom and price runup is significantly different then in "normal" times when neither occurs. This is expected, as predicting crashes are easier than negative future returns.

III.B. HML Portfolios

The natural follow up to our first set of empirical results is to ask whether certain stocks are impacted more severely by the burst of the credit-fueled stock market boom. To answer this question, we sort firms by their characteristics into decile portfolios, and explore the predictive power of the credit-fueled stock market boom on the returns of the High-minus-Low (HML) portfolios. The results allow us to provide empirical evidence for different theories concerning bubbles while also providing useful information for factor-timing, albeit at a low frequency.

We offer empirical evidence for two competing theories on bubbles. We find no evidence for over-extrapolation: the behavioral biases where investors place too much weight on a firm's past success. In Table 8, Panels A & B, we examine the future returns of the momentum HML portfolio and the sales growth portfolio, conditional on a credit-fueled stock market boom. When there is no credit-fueled stock market boom, the momentum HML portfolio is highly profitable on average, yielding around 9% annual returns. The sales-growth portfolio yields slightly above 1% annually on average.

The individual coefficients for large credit booms, high past returns, and their interaction effects are generally not significant, regardless of the time horizon. Furthermore, the total effect

of the credit-fueled stock market boom is not statistically different from zero and is small economically. This implies that the conditional future returns of the momentum HML portfolio and the sales-growth HML portfolio, based on whether or not observing a credit-fueled bubble, do not differ significantly.

We find strong evidence for belief disagreements and collateral constraints. Geanakoplos (2007, 2010) and Simsek (2013) show that belief disagreements impact collateral constraints of investors in the market. When collateral constraints are looser for optimistic (pessimistic) investors, these investors can take on more leverage in the form of debt (short) contracts and have a larger influence on asset prices. When investors and lenders have lower levels of disagreement on the down-side states where investors default on their debt contracts, investors face looser collateral constraints. Thus, a credit boom signifies an environment where optimistic investors have looser collateral constraints, can take on higher levels of leverage, and have a larger influence on stock prices.

Panels C-H of Table 8 provide us with empirical evidence supporting belief disagreements and collateral constraints playing a key role. Interestingly, we find the disagreement effect does not persist market wide but rather is concentrated on young growth firms that are more difficult to value. The Market beta HML portfolio has significantly lower conditional returns following a price run-up (-21.6% over the next three years with a t-stat of -3.99). However, the total effect of the credit-fueled boom is not significantly different from zero. Firms with higher expected growth, as proxied by low Earnings to Price (E/P), Dividend Yield (D/P) and Book to Market (B/M) ratios, are likely to have a more disparate distribution of outcomes. Optimistic investors are attracted by the upside states and place relatively higher valuations of these firms in comparison to value stocks. The importance of the credit boom lies in the fact that optimistic investors find it easier to leverage

their positions and have an outsized impact on growth stocks. If the bubble deflates and the upside state does not materialize, growth stocks experience relatively more stress compared to value stocks. Panel D-F shows that value stocks tend to earn higher average returns in "normal" times. But more importantly, the conditional returns of the HML portfolios are significantly higher. After observing a credit-fueled boom, the E/P HML portfolio has significantly higher average returns over two to three years in the future. The results are very large economically, with the total effect of the credit-fueled boom over 2.7 times as large the unconditional return over three years. The results for the D/P HML portfolio are weaker statistically, only significant at the 10% level, though the magnitude of the effect of the credit-fueled boom is still twice as large in comparison to the unconditional average returns over three years. The results for the B/M HML portfolio are not significant, but the direction of the total effect of the credit-fueled stock market boom is still positive.

Panels G-H present further evidence of the effects of disagreement and collateral constraints. Analyst dispersion measures the degree for which analysts following a firm disagree on its earnings per share for the next financial year. Firms with higher analyst dispersion are likely to have a wider dispersion of outcomes. Optimists are attracted by the high ends and use the loose credit conditions under a credit boom to leverage their positions, bidding up the price of the stock. When the bubble deflates, these stocks experience larger losses in value. Following a credit-fueled boom, the analyst dispersion HML portfolio experiences on average 11.7%, 17.5% and 24.1% lower returns compared to its unconditional mean. The firm age HML portfolio tells a similar story. Younger firms are more difficult to value in contrast to older more mature firms. The firm age HML portfolio 3-year future return is 10.7% higher conditional on a credit-fueled boom.

The results of Panels I-L show the returns of HML portfolios formed on size, equity issuance, stock volatility and turnover. The conditional returns of these HML portfolios do not differ significantly from the unconditional means.

The results of Panel M shows that there is also an economic channel through which credit booms affect stock returns. The credit crunch that follows the credit boom limits the ability of *all* firms to roll-over long term debt and negatively impacts their ability to invest in profitable projects. However, highly leveraged firms rely more on external financing and are particularly sensitive to credit conditions. Highly leveraged firms underperform unconditionally, with their returns over a two to three year horizon to be around 1.5% lower annually (significant at the 1% level) compared to their counterparts with low leverage. The conditional underperformance is far more drastic. In the next one, two and three years following a credit fueled boom, the average returns on the leverage HML portfolio is 7.1%, 14.0% and 17.0% lower than its unconditional mean, and the difference is highly statistically significant.

III.C. Credit Beta Portfolios

Our last set of empirical results examines whether investors can identify stocks which are more sensitive to the credit cycle directly through returns, rather than firm characteristics. To do so, we employ a traditional beta estimation method typically employed in empirical asset pricing.

Estimating credit betas requires that we turn to a higher data frequency for our credit expansion series. We obtain US monthly bank credit series from January 1947 to December 2016, compiled by the Board of Governors of the Federal Reserve System and accessible via the FRED database. To calculate a measure of bank credit to the private sector, we subtract the amount of treasury and agency securities that banks hold from the total bank credit extended. We then generate a monthly

credit expansion series through the same method as our main credit expansion variable. Once annualized, the correlation between this monthly series and our main credit expansion variable is over 90%. We combine the monthly bank credit series with US monthly stock data obtained from CRSP/COMPUSTAT from July 1927 – December 2016.

The credit beta's are estimated at the end of December annually, with $CER_{i,t} = \alpha_{i,t} + \beta_{i,M}\Delta Credit_{t-36} + \epsilon_{i,t}$, where $CER_{i,t} = \sum_{k=t-35}^{t} ER_{i,k}$ is stock $i's$ three year cumulative excess return. $M - 120 \leq t \leq M$.

Tables 9 and 10 present key summary statistics for our estimated credit betas. The fit of our regression is quite good (average *adjusted* R^2 of 0.25), and the credit betas are reasonably persistent up to 5 years (0.40). As seen in Table 10 Panel A, the excess returns on the equal weighted credit beta portfolios exhibit an inverse U-shape. The excess returns for the portfolios with the most extreme exposures to credit expansion (1st and 10th decile portfolio), whether positive or negative, are economically lower in contrast to the 2nd - 9th decile portfolios.

We further investigate by forming cross-sorted portfolios on credit beta and volatility. The results are presented in Table 11. Whether it is equal weighted or market cap weighted portfolios, it is clear that credit beta matters for high volatility stocks. Focusing on stocks within the top 20% of weekly price volatility, the inverse U-pattern emerges once again. Amongst stocks with high volatility (volatility = 5), stocks with large exposures to credit expansion, whether positive (credit beta = 5) or negative (credit beta = 1) underperform. The annual differences with the 3rd credit beta portfolio range from a low of 5.3% to a high of 13.9%.

In Table 12, we examine the excess returns of the credit portfolios, benchmarked against the Fama & French three factor model. Once again, the inverse-U shape emerges without fail. For the equal-weighted portfolios, the monthly alphas for the 1st and 10th portfolio is -0.35% (significant

at 5% level) and -0.52% (significant at 1% level) respectively. For the market-weighted portfolios, the monthly alphas for the 1st and 10th portfolio is -0.28% and -0.31%, though both are only significant at the 10% level.

IV. CONCLUSION

By analyzing 43 economies over 1870 - 2016, we find evidence that large credit expansions interacted with price run-ups, have strong forecasting power for negative future returns. The mean cumulative excess return is -22.1% for the housing market over 6 years, and -15.4% for the stock market over 3 years.

We find strong empirical evidence for belief disagreements and collateral constraints for being the channel through which credit fueled booms influence stock markets. Growth stocks, stocks with high levels of analyst disagreement, and highly leveraged stocks are particularly vulnerable to the bust, with their respective factor portfolios significantly underperforming compared to their unconditional means. There is also an economic channel through which credit booms affect stock returns. The credit crunch that follows the credit boom limits the ability of *all* firms to roll-over long term debt and negatively impacts their ability to invest in profitable projects. However, highly leveraged firms rely more on external financing and are particularly sensitive to credit conditions. Our findings also have important implications for factor timing, particularly with regards to growth vs value strategies.

Finally, we show that by avoiding stocks with extreme exposures to the credit cycle, investors can partially mitigate the risks induced by a credit-fueled boom.

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Table 1
Summary Statistics for Market Returns, Characteristics and Credit Expansion

This table presents summary statistics for market index returns, market characteristics, and credit expansion. Our sample consists of 43 economies and range from 1870 – 2016. Summary statistics on cumulative excess returns across 1-3 years for the stock market, and 4-6 years for the housing market are presented. Also presented are information on our standardized credit expansion measure, and market characteristics including average rental yields, average dividend yield, average stock volatility, average price-to-earnings ratio, average book-to-market ratio, average turnover and past excess returns on the stock market.

	N	Mean	Median	SD	1%	5%	10%	25%	95%	99%
Stock Market Returns										
1 year ahead	3165	0.029	0.033	0.310	-0.886	-0.428	-0.271	-0.103	0.458	0.843
2 year ahead	3068	0.054	0.060	0.427	-1.162	-0.593	-0.406	-0.152	0.682	1.113
3 year ahead	2977	0.083	0.089	0.504	-1.238	-0.697	-0.462	-0.162	0.821	1.368
Housing Market Returns										
4 years ahead	1579	-0.011	-0.028	0.257	-0.662	-0.397	-0.284	-0.151	0.397	0.755
5 years ahead	1535	-0.017	-0.035	0.296	-0.748	-0.474	-0.343	-0.183	0.467	0.841
6 years ahead	1492	-0.022	-0.045	0.331	-0.821	-0.537	-0.390	-0.217	0.520	0.923
Independent Variables										
Credit Expansion	3703	0.010	0.008	0.035	-0.085	-0.035	-0.019	-0.004	0.059	0.104
Rental Yields	1829	0.055	0.052	0.021	0.016	0.028	0.033	0.041	0.093	0.117
Dividend Yield	2952	0.041	0.038	0.023	0.004	0.012	0.016	0.026	0.081	0.122
Stock Volatility	1598	0.012	0.010	0.008	0.002	0.004	0.005	0.007	0.025	0.042
P/E Ratio	1217	16.0	15.0	8.06	5.10	7.20	8.60	11.50	26.70	50.50
Book/Market Ratio	1093	0.66	0.58	0.37	0.22	0.32	0.36	0.46	1.19	2.27
Turnover	1264	0.591	0.467	0.487	0.009	0.077	0.123	0.257	1.637	2.227
Stock Past Returns (3)	2980	0.084	0.089	0.504	-1.238	-0.696	-0.462	-0.162	0.820	1.368
Housing Past Returns (6)	1492	-0.022	-0.045	0.331	-0.821	-0.537	-0.390	-0.217	0.520	0.923

Table 2
Summary Statistics for Individual Stocks in Each Country

The table shows summary statistics of the Thomson Financial's Worldscope stocks in Datastream International which have at least 12 monthly returns and have been listed in the country's major exchange(s) from 1981 to 2019. Number of stocks are the total number of stocks in the sample. Mean and standard deviation of the monthly return (%) for each country are calculated from the equally-weighted portfolio return (in local currency units). The correlation between the value-weighted country returns of our sample and Fama & French value-weighted country returns are also presented. Also reported are the time series average of yearly medians for December-end firm size (in local currency units), firm age, year-end book-to-market (B/M), dividend-to-price (D/P), earnings-to-price (E/P), long-term debt-to-equity (L/B, %), year-on-year sales growth, December-end betas with respect to value-weighted country portfolios, differences in analyst earning-per-share forecasts, amount of equity raised, weekly stock price volatility, annual turnover as a percentage of market capitalization.

		Monthly Returns (%)			Time-series average of											
Country	Total number of stocks	Mean	Std. dev	ρ with FF Country Returns	Median Size (LCmil)	Median age	Median B/M	Median D/P	Median E/P	Median L/B (%)	Median sales growth	Median country beta	Median Analyst dispersion	Median Equity Issuance	Median Annual Volatility	Median Turnover (%)
Australia	1,281	0.50	20.59	91.76%	21	11	0.72	0.02	0.01	16.31	10.95	0.70	0.07	0.02	0.51	0.09
Austria	94	0.49	9.92	97.88%	138	58	0.76	0.02	0.06	46.70	5.70	0.54	0.10	0.01	0.28	0.01
Belgium	180	0.52	9.90	94.72%	117	32	0.81	0.03	0.07	33.61	5.99	0.54	0.08	0.00	0.27	0.01
Canada	3,551	1.49	28.55	86.10%	17	10	0.72	0.01	0.01	23.47	4.97	0.90	0.04	0.03	0.71	0.02
Denmark	220	0.52	10.67	98.54%	485	44	0.92	0.01	0.06	29.82	6.81	0.48	0.09	0.02	0.29	0.02
Finland	179	0.57	10.70	65.88%	115	24	0.85	0.04	0.06	84.46	7.86	0.62	0.09	0.01	0.33	0.04
France	1,093	0.59	13.72	98.51%	101	22	0.64	0.01	0.05	35.94	7.45	0.54	0.08	0.00	0.35	0.02
Germany	1,023	0.30	15.82	97.46%	101	40	0.55	0.01	0.04	17.34	6.48	0.55	0.09	0.00	0.35	0.00
Hong Kong	1,428	0.73	18.66	98.73%	749	12	0.88	0.02	0.07	6.12	10.03	0.90	0.10	0.00	0.53	0.03
Ireland	23	0.63	14.92	89.89%	286	16	0.77	0.03	0.06	44.03	14.13	0.71	0.07	0.07	0.32	0.03
Italy	440	0.15	10.78	97.97%	159	42	0.77	0.02	0.04	27.28	7.90	0.78	0.11	0.01	0.34	0.04
Japan	4,534	0.47	11.67	97.21%	28007	41	0.74	0.01	0.04	22.45	3.17	0.79	0.07	0.00	0.35	0.12
Netherlands	162	0.69	10.76	98.24%	282	48	0.65	0.03	0.07	32.53	5.58	0.68	0.07	0.00	0.30	0.05
New Zealand	185	0.39	12.57	95.81%	113	17	0.73	0.04	0.06	26.29	8.23	0.61	0.07	0.02	0.32	0.01
Norway	318	0.45	13.57	85.90%	594	25	0.76	0.01	0.06	103.44	10.26	0.60	0.11	0.01	0.40	0.04
Singapore	744	0.50	15.25	98.28%	113	15	0.84	0.02	0.05	8.21	6.02	0.90	0.10	0.00	0.42	0.02
Spain	263	0.49	10.48	98.39%	296	40	0.61	0.02	0.05	39.18	8.90	0.68	0.10	0.00	0.34	1.36
Sweden	887	0.75	16.08	87.33%	435	20	0.71	0.02	0.06	36.35	10.55	0.78	0.09	0.01	0.41	0.04
Switzerland	206	0.52	8.83	97.44%	305	56	0.82	0.02	0.06	37.43	4.41	0.61	0.09	0.00	0.27	0.03
U. K.	2,409	0.34	14.47	95.76%	47	20	0.58	0.02	0.05	10.94	8.92	0.75	0.05	0.00	0.37	0.06
U. S. A.	6,358	1.00	14.96	99.07%	299	17	0.52	0.01	0.05	27.43	8.66	0.95	0.03	0.00	0.39	0.11

Table 3
Excess Market Returns against Credit Expansion & Credit Booms

The table presents the results of regressing future cumulative market excess returns on normalized credit expansion or large credit boom. Credit expansion is defined as the annualized past three-year percentage point change in bank credit to GDP. Bank credit is measured as credit extended by the banking sector to domestic households and nonfinancial corporations. We standardize credit expansion using the historical distribution of each country at the given point in time to avoid look ahead bias. The large credit boom indicator takes the value of 1 if credit expansion exceeds the 90th historical distribution of the normalized credit expansion series, and 0 otherwise. Panel A presents results for when the outcome variable is housing market future cumulative excess returns. Panel B presents results for when the outcome variable is stock market future cumulative excess returns. Our sample includes 43 economies from 1870-2016. t-statistics are presented in parenthesis. We employ Driscoll-Kraay standard errors to adjust for clustering of the error term across countries or time. $*\ t < 0.1$; $**\ t < 0.05$; $***\ t < 0.01$.

	1 year ahead		2 years ahead		3 years ahead		4 years ahead		5 years ahead		6 years ahead	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
						Panel A: Housing Market						
Normalized Credit Expansion	0.002		-0.001		-0.008*		-0.015***		-0.022***		-0.026***	
	(0.86)		(-0.40)		(-1.77)		(-2.75)		(-3.34)		(-3.52)	
Large Credit Boom		0.000		-0.021*		-0.048***		-0.081***		-0.111***		-0.128***
		(0.03)		(-1.70)		(-2.94)		(-4.07)		(-4.84)		(-5.02)
Constant (Average Returns)	-0.002	-0.001	-0.003	0.000	-0.003	0.003	-0.004	0.005	-0.006	0.007	-0.008	0.006
	(-0.61)	(-0.52)	(-0.62)	(0.02)	(-0.53)	(0.41)	(-0.53)	(0.69)	(-0.66)	(0.73)	(-0.81)	(0.63)
Total Returns	0.000	-0.001	-0.004	-0.020	-0.011	-0.045	-0.019	-0.075	-0.027	-0.104*	-0.034	-0.122*
	(0.01)	(-0.09)	(-0.20)	(-0.77)	(-0.37)	(-1.16)	(-0.50)	(-1.51)	(-0.60)	(-1.76)	(-0.70)	(-1.91)
N	1450	1450	1406	1406	1364	1364	1323	1323	1282	1282	1241	1241
Adjusted R^2(%)	-0.02	-0.07	-0.06	0.13	0.16	0.56	0.49	1.16	0.79	1.72	0.91	1.91
						Panel B: Stock Market						
Normalized Credit Expansion	-0.025***		-0.043***		-0.055***							
	(-5.74)		(-6.94)		(-7.40)							
Large Credit Boom		-0.070***		-0.104***		-0.137***						
		(-4.19)		(-4.47)		(-4.95)						
Constant (Average Returns)	0.039***	0.045***	0.075***	0.082***	0.113***	0.123***						
	(6.34)	(6.82)	(8.71)	(8.85)	(10.96)	(10.95)						
Total Returns	0.014	-0.025	0.032	-0.022	0.058*	-0.015						
	(0.92)	(-0.95)	(1.28)	(-0.61)	(1.69)	(-0.34)						
N	2570	2570	2484	2484	2404	2404						
Adjusted R^2(%)	1.23	0.64	1.86	0.76	2.19	0.97						

Table 4
Two-way Tabulation of Credit Boom & Time Series Variables

This table presents two-way cross tabulation of credit booms and years when a market characteristic is high or low. Credit expansion is defined as the annualized past three-year percentage point change in bank credit to GDP. Bank credit is measured as credit extended by the banking sector to domestic households and nonfinancial corporations. We standardize credit expansion using the historical distribution of each country at the given point in time to avoid look ahead bias. The large credit boom indicator takes the value of 1 if credit expansion exceeds the 90th historical distribution of the normalized credit expansion series, and 0 otherwise. The "high" indicators take the value of 1 if the characteristic exceeds the 90th percentile of its historical distribution, and 0 otherwise. The "low" indicators take the value of 1 if the characteristic is below the 10th percentile of its historical distribution, and 0 otherwise.

	Low Rent Yield		Low Div Yield		High Stock Vol		High PE Ratio		Low Book/Market		High Turnover		High Past Returns	
Credit Boom	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
No	843	403	1126	824	848	330	563	336	561	256	451	478	1403	703
Yes	115	82	181	149	168	73	118	75	97	65	55	127	216	144
Sum	958	485	1307	973	1016	403	681	411	658	321	506	605	1619	847
Total	1443		2280		1419		1092		979		1111		2466	

Table 5
Excess Housing Price Returns against Large Credit Booms and Interactions

This table presents the results of regressing housing market future cumulative excess returns on large credit boom and market characteristic indicators. Credit expansion is defined as the annualized past three-year percentage point change in bank credit to GDP. Bank credit is measured as credit extended by the banking sector to domestic households and nonfinancial corporations. We standardize credit expansion using the historical distribution of each country at the given point in time to avoid look ahead bias. The large credit boom indicator takes the value of 1 if credit expansion exceeds the 90th historical distribution of the normalized credit expansion series, and 0 otherwise. The high past excess returns indicator takes the value of 1 if cumulative returns over the past 6 years exceed the 90th percentile of the historical distribution, and 0 otherwise. The low rental yield indicator takes the value of 1 if rental yields at year end is below the 10th percentile of the historical distribution, and 0 otherwise. Our sample includes 43 economies from 1870-2016. t-statistics are presented in parenthesis. We employ Driscoll-Kraay standard errors to adjust for clustering of the error term across countries or time. $*\ t < 0.1$; $**\ t < 0.05$; $***\ t < 0.01$.

	1 year ahead		2 years ahead		3 years ahead		4 years ahead		5 years ahead		6 years ahead	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Panel A: Large Credit Booms and High Past Returns												
High Past Excess Returns	0.039***	0.044***	0.046***	0.065***	0.038**	0.075***	0.033*	0.085***	0.036*	0.092***	0.044*	0.097***
	(6.05)	(6.05)	(4.18)	(5.22)	(2.51)	(4.44)	(1.79)	(4.10)	(1.65)	(3.82)	(1.81)	(3.60)
Large Credit Boom		-0.001		-0.009		-0.016		-0.039*		-0.071***		-0.093***
		(-0.19)		(-0.64)		(-0.90)		(-1.74)		(-2.77)		(-3.26)
Interaction Term		-0.021		-0.081***		-0.161***		-0.219***		-0.225***		-0.210***
		(-1.28)		(-2.89)		(-4.25)		(-4.75)		(-4.25)		(-3.52)
Constant (Average Returns)	-0.009***	-0.009***	-0.013***	-0.012**	-0.015**	-0.013**	-0.019**	-0.014*	-0.024***	-0.014	-0.028***	-0.015
	(-3.39)	(-3.10)	(-2.90)	(-2.49)	(-2.44)	(-1.97)	(-2.43)	(-1.65)	(-2.62)	(-1.43)	(-2.74)	(-1.33)
Total Returns	0.030***	0.013	0.033	-0.037	0.023	-0.116	0.015	-0.187*	0.012	-0.218*	0.016	-0.221*
	(0.03)	(0.48)	(1.60)	(-0.75)	(0.68)	(-1.55)	(0.30)	(-1.88)	(0.19)	(-1.90)	(0.22)	(-1.83)
N	1329	1329	1290	1290	1253	1253	1217	1217	1181	1181	1145	1145
Adjusted R^2(%)	2.61	2.65	1.26	2.15	0.42	2.56	0.18	3.49	0.15	3.91	0.20	3.74
Panel B: Large Credit Booms and Low Rent Yield												
Low Rental Yield	-0.004	-0.002	-0.017	-0.012	-0.030**	-0.025	-0.037**	-0.033*	-0.050**	-0.049**	-0.069***	-0.072***
	(-0.73)	(-0.31)	(-1.61)	(-1.06)	(-2.11)	(-1.65)	(-2.12)	(-1.71)	(-2.44)	(-2.16)	(-2.92)	(-2.79)
Large Credit Boom		-0.006		-0.028**		-0.061***		-0.101***		-0.142***		-0.172***
		(-0.73)		(-2.05)		(-3.28)		(-4.46)		(-5.45)		(-5.89)
Interaction Term		-0.011		-0.018		-0.006		0.004		0.032		0.069
		(-0.69)		(-0.64)		(-0.16)		(0.08)		(0.61)		(1.16)
Constant (Average Returns)	-0.002	-0.002	-0.003	0.001	-0.004	0.004	-0.007	0.007	-0.009	0.011	-0.009	0.016
	(-0.86)	(-0.55)	(-0.59)	(0.19)	(-0.59)	(0.65)	(-0.86)	(0.85)	(-0.98)	(1.12)	(-0.85)	(1.43)
Total Returns	-0.007	-0.021	-0.019	-0.057	-0.034	-0.088	-0.044	-0.123	-0.059	-0.147	-0.078	-0.160
	(-0.56)	(-0.77)	(-0.84)	(-1.11)	(-1.01)	(-1.24)	(-1.05)	(-1.38)	(-1.24)	(-1.52)	(-1.56)	(-1.60)
N	1270	1270	1231	1231	1194	1194	1158	1158	1123	1123	1088	1088
Adjusted R^2(%)	-0.04	-0.03	0.13	0.61	0.29	1.37	0.30	2.32	0.44	3.32	0.69	3.94

Table 6
Excess Stock Total Returns against Large Credit Boom & Interaction

This table presents the results of regressing stock market future cumulative excess returns on large credit boom and market characteristic indicators. Credit expansion is defined as the annualized past three-year percentage point change in bank credit to GDP. Bank credit is measured as credit extended by the banking sector to domestic households and nonfinancial corporations. We standardize credit expansion using the historical distribution of each country at the given point in time to avoid look ahead bias. The large credit boom indicator takes the value of 1 if credit expansion exceeds the 90th historical distribution of the normalized credit expansion series, and 0 otherwise. The high past excess returns indicator takes the value of 1 if cumulative returns over the past 6 years exceed the 90th percentile of the historical distribution, and 0 otherwise. The "high" indicators take the value of 1 if the characteristic exceeds the 90th percentile of its historical distribution, and 0 otherwise. The "low" indicators take the value of 1 if the characteristic is below the 10th percentile of its historical distribution, and 0 otherwise. Our sample includes 43 economies from 1870-2016. t-statistics are presented in parenthesis. We employ Driscoll-Kraay standard errors to adjust for clustering of the error term across countries or time. $* \; t < 0.1$; $** \; t < 0.05$; $*** \; t < 0.01$.

	1 year ahead		2 years ahead		3 years ahead	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: High Past Excess Return						
High Past Excess Return	-0.009	-0.008	-0.091***	-0.080***	-0.168***	-0.164***
	(-0.56)	(-0.50)	(-4.12)	(-3.31)	(-6.25)	(-5.61)
Large Credit Boom		-0.063***		-0.086***		-0.144***
		(-3.53)		(-3.32)		(-4.63)
Interaction Term		0.006		-0.051		-0.002
		(0.16)		(-0.86)		(-0.03)
Constant (Average Returns)	0.036***	0.045***	0.086***	0.099***	0.134***	0.156***
	(5.61)	(6.54)	(9.29)	(9.88)	(11.96)	(12.88)
Total Returns	0.027	-0.020	-0.005	-0.118*	-0.033	-0.154**
	(1.46)	(-0.52)	(-0.18)	(-1.89)	(-0.67)	(-2.36)
N	2297	2297	2224	2224	2156	2156
Adjusted R^2(%)	-0.03	0.53	0.71	1.41	1.74	2.85
Panel B: Low Dividend Yield						
Low Dividend Yield	-0.037**	-0.039**	-0.105***	-0.097***	-0.132***	-0.132***
	(-2.37)	(-2.28)	(-4.87)	(-4.17)	(-5.12)	(-4.77)
Large Credit Boom		-0.067***		-0.098***		-0.172***
		(-3.42)		(-3.60)		(-5.34)
Interaction Term		0.008		-0.058		-0.010
		(0.19)		(-0.96)		(-0.14)
Constant (Average Returns)	0.050***	0.060***	0.105***	0.120***	0.150***	0.178***
	(7.02)	(7.82)	(10.62)	(11.23)	(12.57)	(13.77)
Total Returns	0.013	-0.038	-0.000	-0.132**	0.018	-0.136**
	(0.60)	(-1.20)	(-0.00)	(-2.34)	(0.35)	(-2.39)
N	1928	1928	1867	1867	1808	1808
Adjusted R^2(%)	0.24	0.85	1.20	2.21	1.37	3.24
Panel C: High Daily Stock Volatility						
High Daily Stock Volatility	0.063***	0.061**	0.051	0.033	-0.076**	-0.101**
	(2.64)	(2.26)	(1.58)	(0.91)	(-2.02)	(-2.41)
Large Credit Boom		-0.081***		-0.137***		-0.214***
		(-3.16)		(-3.98)		(-5.36)
Interaction Term		0.039		0.128		0.180**
		(0.67)		(1.62)		(1.97)
Constant (Average Returns)	0.033***	0.045***	0.073***	0.093***	0.131***	0.163***
	(3.66)	(4.60)	(5.93)	(7.04)	(9.09)	(10.56)
Total Returns	0.096**	0.064	0.124**	0.117	0.055	0.029
	(2.16)	(1.03)	(2.11)	(1.61)	(1.09)	(0.35)
N	1197	1197	1158	1158	1120	1120
Adjusted R^2(%)	0.50	1.21	0.13	1.32	0.27	2.62

Table 6
Excess Stock Total Returns against Large Credit Boom & Interaction (Continued)

	1 year ahead		2 years ahead		3 years ahead	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel D: Low Daily Stock Volatility						
Low Daily Stock Volatility	0.040	0.026	0.066	0.033	0.073	0.051
	(1.31)	(0.80)	(1.62)	(0.76)	(1.48)	(0.99)
Large Credit Boom		-0.073***		-0.122***		-0.188***
		(-3.08)		(-3.83)		(-5.08)
Interaction Term		0.094		0.240*		0.102
		(0.98)		(1.89)		(0.67)
Constant (Average Returns)	0.039***	0.051***	0.074***	0.094***	0.114***	0.145***
	(4.42)	(5.30)	(6.29)	(7.33)	(8.21)	(9.65)
Total Returns	0.079**	0.097	0.141**	0.245	0.187**	0.111
	(2.05)	(0.92)	(2.05)	(1.56)	(2.24)	(0.50)
N	1197	1197	1158	1158	1120	1120
Adjusted R^2(%)	0.06	0.68	0.14	1.30	0.11	2.22
Panel E: High PE Ratio						
High PE Ratio	-0.045**	-0.059**	-0.078**	-0.091***	-0.089**	-0.119***
	(-1.97)	(-2.36)	(-2.55)	(-2.69)	(-2.51)	(-3.08)
Large Credit Boom		-0.086***		-0.134***		-0.246***
		(-2.95)		(-3.43)		(-5.54)
Interaction Term		0.086		0.079		0.176**
		(1.46)		(1.00)		(1.97)
Constant (Average Returns)	0.052***	0.066***	0.102***	0.124***	0.149***	0.193***
	(4.74)	(5.55)	(6.88)	(7.72)	(8.65)	(10.32)
Total Returns	0.007	0.007	0.024	-0.021	0.060	0.003
	(0.22)	(0.30)	(0.35)	(-0.36)	(0.57)	(0.04)
N	860	860	826	826	792	792
Adjusted R^2(%)	0.33	1.11	0.66	1.90	0.67	4.24
Panel F: Low Book/Market						
Low Book/Market	-0.067**	-0.057*	-0.106***	-0.118***	-0.208***	-0.235***
	(-2.19)	(-1.70)	(-2.62)	(-2.63)	(-4.51)	(-4.65)
Large Credit Boom		-0.064**		-0.127***		-0.231***
		(-2.00)		(-2.98)		(-4.82)
Interaction Term		-0.036		0.089		0.182
		(-0.46)		(0.87)		(1.59)
Constant (Average Returns)	0.043***	0.053***	0.088***	0.108***	0.147***	0.184***
	(3.73)	(4.22)	(5.69)	(6.43)	(8.19)	(9.55)
Total Returns	-0.024	-0.104	-0.018	-0.048	-0.061	-0.100
	(-0.34)	(-0.85)	(-0.16)	(-0.41)	(-0.40)	(-0.83)
N	752	752	719	719	686	686
Adjusted R^2(%)	0.51	1.03	0.81	1.78	2.75	5.70

Table 6
Excess Stock Total Returns against Large Credit Boom & Interaction (Continued)

	Panel G: High Turnover					
	1 year ahead		2 years ahead		3 years ahead	
	(1)	(2)	(3)	(4)	(5)	(6)
High Turnover	-0.037*	-0.018	-0.064**	-0.051*	-0.135***	-0.138***
	(-1.77)	(-0.75)	(-2.27)	(-1.65)	(-4.15)	(-3.84)
Large Credit Boom		-0.022		-0.096*		-0.233***
		(-0.56)		(-1.81)		(-3.86)
Interaction Term		-0.075		-0.006		0.117
		(-1.34)		(-0.08)		(1.39)
Constant (Average Returns)	0.052***	0.055***	0.093***	0.105***	0.156***	0.186***
	(4.07)	(4.02)	(5.39)	(5.70)	(7.67)	(8.62)
Total Returns	0.015	-0.060	0.030	-0.048	0.021	-0.067
	(0.30)	(-0.88)	(0.42)	(-0.64)	(0.25)	(-0.74)
N	844	844	807	807	771	771
Adjusted R^2(%)	0.25	0.76	0.51	1.14	2.06	4.15

Table 7

Table 7, Panel A and B provide information on the probability of a housing market crash or stock market crash conditional on observing a credit boom or price runup. A market crash is defined as an episode where the return is below -30%. The large credit boom indicator takes the value of 1 if credit expansion exceeds the 90th historical distribution of the normalized credit expansion series, and 0 otherwise. The price runup indicator takes the value of 1 if cumulative returns over the past 6 years exceed the 90th percentile of the historical distribution, and 0 otherwise. Our sample includes 43 economies from 1870-2016.

Panel A
Summary of Crash Episodes

	Total Episodes	Preceded by Credit Boom	Preceded by Price Runup	Preceded by Credit Boom and Price Runup	No Credit Boom nor Price Runup
Housing Market					
Crashes	202	53(26.2%)	46(22.8%)	18(8.9%)	85(42.1%)
Non-Crashes	1,097	118(10.8%)	167(15.2%)	22(2.0%)	790(72.0%)
Stock Market					
Crashes	524	106(20.2%)	151(28.8%)	38(7.3%)	229(43.7%)
Non-Crashes	1,814	227(12.5%)	243(13.4%)	32(1.8%)	1312(72.3%)

Panel B
Probit regressions of Market Crash Episodes

		1 years ahead		2 years ahead		3 years ahead		4 years ahead		5 years ahead		6 years ahead	
		(1) Crash Dummy	(2) Boom Dummy	(3) Crash Dummy	(4) Boom Dummy	(5) Crash Dummy	(6) Boom Dummy	(7) Crash Dummy	(8) Boom Dummy	(9) Crash Dummy	(10) Boom Dummy	(11) Crash Dummy	(12) Boom Dummy
Housing Market													
Individual	Large Credit Boom	0.029*	0.018	0.061*	-0.023	0.086***	-0.053	0.119**	-0.134**	0.191***	-0.218***	0.143***	0.008
		(1.73)	(1.15)	(1.96)	(-0.69)	(3.17)	(-0.72)	(2.31)	(-2.25)	(3.72)	(-2.77)	(2.73)	(0.09)
	N	1,450	1,450	720	720	472	472	360	360	288	288	228	228
Individual	Price Runup	-0.011	0.042*	-0.016	0.038	0.013	0.029	-0.002	0.004	0.043	-0.074	0.006	0.062
		(-0.66)	(1.80)	(-0.51)	(0.95)	(0.35)	(0.56)	(-0.03)	(0.05)	(1.05)	(-0.68)	(0.12)	(0.59)
	N	1,301	1,301	641	641	427	427	313	313	246	246	201	201
Combined	Large Credit Boom	0.041**	-0.002	0.061	-0.074	0.083***	-0.087	0.137**	-0.109	0.211***	-0.191	0.148**	-0.144
		(2.46)	(-0.11)	(1.54)	(-1.17)	(2.92)	(-0.92)	(2.06)	(-1.16)	(7.67)	(-1.46)	(2.15)	(-1.02)
	Price Runup	-0.025	0.037	-0.112*	0.023	-0.024	0.002	-0.045	0.017	-0.006	-0.084	-0.074	-0.022
		(-1.28)	(1.23)	(-1.80)	(0.39)	(-0.45)	(0.03)	(-0.52)	(0.20)	(-0.09)	(-0.57)	(-1.09)	(-0.19)
	Interaction	0.003	0.024	0.133	0.115	0.077	0.162	0.007	0.003	0.002	0.182	0.102	0.359*
		(0.08)	(1.06)	(1.46)	(1.43)	(0.97)	(1.36)	(0.05)	(0.02)	(0.01)	(0.71)	(0.68)	(1.89)
	N	1,233	1,233	607	607	404	404	296	296	231	231	190	190
Stock Market													
Individual	Large Credit Boom	0.061***	-0.027*	0.067*	-0.049	0.134***	-0.015						
		(2.61)	(-1.70)	(1.88)	(-1.34)	(2.83)	(-0.37)						
	N	2,570	2,570	1,241	1,241	773	773						
Individual	Price Runup	0.017	0.014	0.054*	-0.001	0.176***	-0.071						
		(1.07)	(0.68)	(1.78)	(-0.04)	(3.55)	(-1.30)						
	N	2,558	2,558	1,238	1,238	794	794						
Combined	Large Credit Boom	0.057**	-0.030*	0.062	-0.061*	0.136**	-0.090*						
		(2.26)	(-1.75)	(1.53)	(-1.75)	(2.47)	(-1.68)						
	Price Runup	0.007	0.010	0.050	-0.010	0.182***	-0.141**						
		(0.35)	(0.49)	(1.36)	(-0.24)	(3.91)	(-2.13)						
	Interaction	0.015	-0.003	0.010	0.013	0.033	0.207						
		(0.38)	(-0.09)	(0.10)	(0.22)	(0.33)	(1.63)						
	N	2,297	2,297	1,110	1,110	696	696						

Table 8
HML portfolio returns against Credit Expansion

We construct our high-minus-low (HML) portfolios by sorting stocks by their characteristics. To ensure that stocks are sorted into portfolios based on observable data in real time, we follow Fama and French (1992) and match financial statement data for fiscal year-end in year $t-1$ with monthly returns from December of year t to November of year $t+1$. Our book-to-market (B/M), dividend yield (D/P), earnings-to-price (E/P) portfolios are computed using a firm's market capitalization reported by Datastream at the end of December of year t. Size is defined as the market equity at the end of December in year t. Firm age is the time since a firm's establishment or incorporation. Leverage is long term debt divided by common equity. Equity issuance is net proceeds from Sale/Issue of common and preferred stock in year $t-1$ divided by market capitalization in December of year $t-2$. Stock volatility is the standard deviation of end-of-week stock prices divided by their mean from January to December of year t. Market Betas are estimated annually for each stock at the end of December each year, using its previous 60 monthly returns, with a minimum of 30 monthly returns. Analyst dispersion measures disagreement in analyst earnings per share forecasts for the next financial year. It is the standard deviation of all analyst earnings per share forecasts for a company divided by their mean Momentum for month $q+1$ is the cumulative return from month $q-11$ to month $q-1$, we skip the return of month q to mitigate bid-ask bounces, short term reversals or nonsynchronous trading. The large credit boom indicator takes the value of 1 if credit expansion exceeds the 90th historical distribution of the normalized credit expansion series, and 0 otherwise. The high past excess returns indicator takes the value of 1 if cumulative returns over the past 6 years exceed the 90th percentile of the historical distribution, and 0 otherwise. Our sample includes 20 economies from 1981-2019. t-statistics are presented in parenthesis. We employ Driscoll-Kraay standard errors to adjust for clustering of the error term across countries or time. $*\ t<0.1$; $**\ t<0.05$; $***\ t<0.01$.

Panel A: Momentum

	(1) 1-year future	(2) 2-year future	(3) 3-year future	(4) 1-year future	(5) 2-year future	(6) 3-year future
Large Credit Boom	1.462	3.890	5.461	1.332	5.143	6.612
	(0.53)	(1.04)	(1.22)	(0.44)	(1.23)	(1.32)
High Past Returns				-3.585	-1.629	-8.301
				(-1.07)	(-0.35)	(-1.48)
Interaction Term				2.060	-5.186	-2.039
				(0.29)	(-0.54)	(-0.18)
Constant (Average Returns)	8.970***	18.381***	27.709***	9.417***	18.578***	28.758***
	(8.07)	(12.08)	(14.87)	(7.92)	(11.44)	(14.44)
Total Effect of Credit Bubble				-0.193	-1.672	-3.728
				(-0.02)	(-0.18)	(-0.26)
N	585	565	545	585	565	545
Adjusted R^2(%)	-0.12	0.02	0.09	-0.26	-0.20	0.32

Panel B: Sales Growth

	(1) 1-year future	(2) 2-year future	(3) 3-year future	(4) 1-year future	(5) 2-year future	(6) 3-year future
Large Credit Boom	-0.411	-1.069	-1.422	-0.082	-0.293	-1.642
	(-0.18)	(-0.34)	(-0.38)	(-0.03)	(-0.09)	(-0.40)
High Past Returns				5.519**	4.779	1.477
				(2.02)	(1.30)	(0.33)
Interaction Term				-3.455	-5.812	0.842
				(-0.55)	(-0.69)	(0.08)
Constant (Average Returns)	0.889	1.898	3.419**	0.200	1.302	3.235**
	(0.98)	(1.57)	(2.34)	(0.21)	(1.00)	(2.07)
Total Effect of Credit Bubble				1.982	-1.326	0.676
				(0.42)	(-0.22)	(0.10)
N	567	567	567	567	567	567
Adjusted R2(%)	-0.17	-0.16	-0.15	0.22	-0.21	-0.48

			Panel C: Market Beta			
	(1)	(2)	(3)	(4)	(5)	(6)
	1-year future	2-year future	3-year future	1-year future	2-year future	3-year future
Large Credit Boom	2.169	3.240	5.217	2.696	3.878	2.961
	(0.76)	(0.84)	(1.14)	(0.86)	(0.92)	(0.60)
High Past Returns				-0.755	-8.732*	-21.613***
				(-0.22)	(-1.90)	(-3.99)
Interaction Term				-2.762	-1.034	19.187
				(-0.36)	(-0.10)	(1.58)
Constant (Average Returns)	0.910	1.777	2.402	1.003	2.862*	5.086***
	(0.81)	(1.17)	(1.33)	(0.83)	(1.77)	(2.66)
Total Effect of Credit Bubble				-0.822	-5.887	0.535
				(-0.19)	(-0.63)	(0.02)
N	544	544	544	544	544	544
Adjusted R2(%)	-0.08	-0.05	0.06	-0.39	0.45	2.57
			Panel D: Earnings to Price			
	(1)	(2)	(3)	(4)	(5)	(6)
	1-year future	2-year future	3-year future	1-year future	2-year future	3-year future
Large Credit Boom	0.843	4.889	6.117	0.303	2.941	2.218
	(0.35)	(1.36)	(1.36)	(0.11)	(0.71)	(0.43)
High Past Returns				4.056	11.490***	13.987***
				(1.42)	(2.70)	(2.64)
Interaction Term				0.999	4.157	11.775
				(0.17)	(0.47)	(1.08)
Constant (Average Returns)	4.077***	7.628***	12.206***	3.493***	5.980***	10.117***
	(4.03)	(5.07)	(6.40)	(3.18)	(3.69)	(4.91)
Total Effect of Credit Bubble				5.358	18.588***	27.980***
				(1.44)	(3.23)	(5.16)
N	646	627	608	642	623	604
Adjusted R2(%)	-0.14	0.14	0.14	0.01	1.65	2.15
			Panel E: Dividend Yield			
	(1)	(2)	(3)	(4)	(5)	(6)
	1-year future	2-year future	3-year future	1-year future	2-year future	3-year future
Large Credit Boom	2.128	4.725	3.774	1.378	3.737	3.341
	(0.88)	(1.32)	(0.86)	(0.49)	(0.91)	(0.67)
High Past Returns				5.240*	11.140***	18.384***
				(1.84)	(2.63)	(3.56)
Interaction Term				1.190	-0.612	-3.831
				(0.20)	(-0.07)	(-0.36)
Constant (Average Returns)	3.603***	6.876***	11.565***	2.859***	5.305***	8.811***
	(3.57)	(4.60)	(6.21)	(2.61)	(3.28)	(4.39)
Total Effect of Credit Bubble				7.808	14.265*	17.894*
				(1.63)	(1.73)	(1.81)
N	646	627	608	642	623	604
Adjusted R2(%)	-0.04	0.12	-0.04	0.41	1.19	2.11

			Panel F: Book to Market			
	(1)	(2)	(3)	(4)	(5)	(6)
	1-year future	2-year future	3-year future	1-year future	2-year future	3-year future
Large Credit Boom	-2.636	-3.244	-5.987	-2.972	-3.731	-6.152
	(-1.02)	(-0.85)	(-1.29)	(-1.00)	(-0.86)	(-1.16)
High Past Returns				4.561	10.966**	15.458***
				(1.52)	(2.46)	(2.84)
Interaction Term				-0.665	-1.211	-4.077
				(-0.10)	(-0.13)	(-0.36)
Constant (Average Returns)	4.998***	9.191***	14.385***	4.318***	7.571***	12.051***
	(4.73)	(5.89)	(7.45)	(3.77)	(4.50)	(5.77)
Total Effect of Credit Bubble				0.925	6.023	5.229
				(0.16)	(0.93)	(0.68)
N	682	662	642	678	658	638
Adjusted R2(%)	0.01	-0.04	0.11	0.13	0.76	1.22
			Panel G: Analyst Dispersion			
	(1)	(2)	(3)	(4)	(5)	(6)
	1-year future	2-year future	3-year future	1-year future	2-year future	3-year future
Large Credit Boom	-4.061*	-4.157	-4.287	-2.631	-1.612	-1.382
	(-1.90)	(-1.38)	(-1.18)	(-1.12)	(-0.49)	(-0.35)
High Past Returns				-1.865	-2.760	-10.197**
				(-0.73)	(-0.77)	(-2.38)
Interaction Term				-7.246	-13.109	-12.480
				(-1.27)	(-1.62)	(-1.30)
Constant (Average Returns)	-0.061	-0.850	-1.721	0.154	-0.530	-0.532
	(-0.07)	(-0.74)	(-1.24)	(0.18)	(-0.43)	(-0.36)
Total Effect of Credit Bubble				-11.742***	-17.481***	-24.059**
				(-3.74)	(-4.67)	(-2.28)
N	498	495	492	498	495	492
Adjusted R2(%)	0.52	0.18	0.08	0.86	0.86	2.19
			Panel H: Firm Age			
	(1)	(2)	(3)	(4)	(5)	(6)
	1-year future	2-year future	3-year future	1-year future	2-year future	3-year future
Large Credit Boom	5.247**	4.003	2.151	5.293**	2.304	0.583
	(2.29)	(1.19)	(0.54)	(2.11)	(0.63)	(0.13)
High Past Returns				-3.350	-4.938	-0.328
				(-1.26)	(-1.27)	(-0.07)
Interaction Term				-0.988	10.281	10.452
				(-0.16)	(1.10)	(0.95)
Constant (Average Returns)	-1.007	-0.966	-0.527	-0.498	-0.214	-0.478
	(-1.06)	(-0.69)	(-0.32)	(-0.48)	(-0.14)	(-0.27)
Total Effect of Credit Bubble				0.955	7.648	10.707***
				(0.21)	(1.54)	(3.38)
N	675	674	673	674	673	672
Adjusted R2(%)	0.62	0.06	-0.11	0.61	0.05	-0.25

			Panel I: Market Cap			
	(1)	(2)	(3)	(4)	(5)	(6)
	1-year future	2-year future	3-year future	1-year future	2-year future	3-year future
Large Credit Boom	2.674	3.839	6.409	3.179	3.083	5.912
	(1.12)	(1.09)	(1.48)	(1.23)	(0.81)	(1.26)
High Past Returns				0.806	-5.389	-7.858
				(0.29)	(-1.31)	(-1.55)
Interaction Term				-3.439	5.519	4.002
				(-0.51)	(0.55)	(0.33)
Constant (Average Returns)	-3.099***	-6.069***	-8.874***	-3.209***	-5.332***	-7.799***
	(-3.23)	(-4.28)	(-5.08)	(-3.11)	(-3.49)	(-4.15)
Total Effect of Credit Bubble				0.547	3.213	2.056
				(0.13)	(0.51)	(0.25)
N	619	619	619	619	619	619
Adjusted R2(%)	0.04	0.03	0.19	-0.24	-0.02	0.27
			Panel J: Equity Issuance			
	(1)	(2)	(3)	(4)	(5)	(6)
	1-year future	2-year future	3-year future	1-year future	2-year future	3-year future
Large Credit Boom	-0.555	2.404	1.942	-0.241	5.326*	3.271
	(-0.28)	(0.92)	(0.64)	(-0.11)	(1.87)	(0.99)
High Past Returns				1.563	2.794	-0.066
				(0.65)	(0.90)	(-0.02)
Interaction Term				-2.309	-17.563**	-7.544
				(-0.43)	(-2.49)	(-0.92)
Constant (Average Returns)	-0.794	-1.981**	-2.701**	-0.977	-2.308**	-2.693**
	(-1.03)	(-1.97)	(-2.32)	(-1.19)	(-2.17)	(-2.17)
Total Effect of Credit Bubble				-0.987	-9.443	-4.339
				(-0.24)	(-1.49)	(-1.18)
N	501	501	501	501	501	501
Adjusted R2(%)	-0.19	-0.03	-0.12	-0.50	0.82	-0.30
			Panel K: Volatility			
	(1)	(2)	(3)	(4)	(5)	(6)
	1-year future	2-year future	3-year future	1-year future	2-year future	3-year future
Large Credit Boom	-2.491	-3.992	-3.074	-3.077	-4.237	-2.586
	(-0.89)	(-1.01)	(-0.66)	(-1.02)	(-0.99)	(-0.51)
High Past Returns				1.857	1.598	-2.238
				(0.57)	(0.35)	(-0.41)
Interaction Term				3.742	1.496	-3.065
				(0.47)	(0.13)	(-0.23)
Constant (Average Returns)	2.869**	5.609***	7.713***	2.614**	5.391***	8.020***
	(2.55)	(3.53)	(4.10)	(2.16)	(3.15)	(3.95)
Total Effect of Credit Bubble				2.522	-1.143	-7.889
				(0.38)	(-0.10)	(-0.72)
N	618	618	618	618	618	618
Adjusted R2(%)	-0.03	0.00	-0.09	-0.21	-0.29	-0.36

			Panel L: Turnover			
	(1)	(2)	(3)	(4)	(5)	(6)
	1-year future	2-year future	3-year future	1-year future	2-year future	3-year future
Large Credit Boom	0.973	1.669	2.479	2.282	2.954	2.136
	(0.33)	(0.39)	(0.47)	(0.70)	(0.62)	(0.37)
High Past Returns				4.155	4.475	-2.818
				(1.20)	(0.89)	(-0.46)
Interaction Term				-8.228	-8.197	2.679
				(-1.06)	(-0.73)	(0.19)
Constant (Average Returns)	-2.998**	-5.776***	-8.614***	-3.543***	-6.364***	-8.244***
	(-2.56)	(-3.42)	(-4.14)	(-2.82)	(-3.50)	(-3.68)
Total Effect of Credit Bubble				-1.791	-0.768	1.997
				(-0.17)	(-0.08)	(0.18)
N	307	307	307	307	307	307
Adjusted R^2(%)	-0.29	-0.28	-0.25	-0.37	-0.63	-0.85
			Panel M: Leverage			
	(1)	(2)	(3)	(4)	(5)	(6)
	1-year future	2-year future	3-year future	1-year future	2-year future	3-year future
Large Credit Boom	-1.558	0.365	1.416	-0.775	2.257	3.341
	(-0.67)	(0.11)	(0.37)	(-0.30)	(0.64)	(0.80)
High Past Returns				-2.107	-6.151	-11.292**
				(-0.76)	(-1.59)	(-2.49)
Interaction Term				-4.262	-10.056	-9.073
				(-0.66)	(-1.13)	(-0.87)
Constant (Average Returns)	-1.645*	-3.891***	-6.052***	-1.378	-3.111**	-4.620***
	(-1.78)	(-3.02)	(-3.98)	(-1.39)	(-2.26)	(-2.86)
Total Effect of Credit Bubble				-7.143*	-13.951***	-17.024***
				(-1.78)	(-5.05)	(-3.27)
N	580	580	580	580	580	580
Adjusted R^2(%)	-0.10	-0.17	-0.15	-0.13	0.62	1.36

Table 9
Fit and Persistence of Credit Betas

This table presents the fit and the persistence of the credit beta. We use 10 year rolling window regressions for estimating the credit beta. A minimum of 3 years data is required for a valid estimation. The credit beta is estimated at the end of December each year by: $CER_{i,t} = \alpha_{i,t} + \beta_{i,M}\Delta Credit_{t-36} + \epsilon_{i,t}$, where $CER_{i,t} = \sum_{k=t-35}^{t} ER_{i,k}$ is stock $i's$ three year cumulative excess return. $M - 120 \leq t \leq M$.

Panel A: *Adjusted* R^2 summary statistics

Mean	SD	Min	5%	10%	25%	Median	75%	90%	95%
0.25	0.19	0	0.03	0.05	0.11	0.20	0.34	0.52	0.65

Panel B: Persistence

ρ_1	ρ_2	ρ_3	ρ_4	ρ_5	ρ_{10}	ρ_{15}	ρ_{20}
0.90	0.75	0.62	0.50	0.40	-0.02	-0.05	-0.03

Table 10
Summary Statistics of Credit Beta Portfolios

This table presents summary statistics for the three-year cumulative excess returns of portfolios formed by sorting firms by their credit betas. Returns are in decile points. We use 10 year rolling window regressions for estimating the credit beta. A minimum of 3 years data is required for a valid estimation. The credit beta is estimated by: $CER_{i,t} = \alpha_{i,t} + \beta_{i,M}\Delta Credit_{t-36} + \epsilon_{i,t}$, where $CER_{i,t} = \sum_{k=t-35}^{t} ER_{i,k}$ is stock $i's$ three year cumulative excess return. $M - 120 \leq t \leq M$. We present summary statistics of both equal weighted and market weighted portfolios.

Panel A: Equal Weighted Credit Beta Portfolios

β Sort	Average β	Mean	SD	Skew	Kurt	Min	5%	10%	25%	Median	75%	90%	95%	Max
1	-1.87	0.22	0.34	0.58	3.52	-0.48	-0.31	-0.17	-0.01	0.20	0.39	0.65	0.85	1.40
2	-0.36	0.28	0.34	0.76	3.68	-0.39	-0.24	-0.07	0.07	0.21	0.44	0.71	0.96	1.20
3	-0.22	0.29	0.32	0.17	2.65	-0.42	-0.29	-0.12	0.07	0.29	0.46	0.78	0.86	0.99
4	-0.14	0.30	0.31	0.23	2.61	-0.43	-0.22	-0.07	0.07	0.34	0.45	0.73	0.93	1.00
5	-0.07	0.30	0.28	-0.07	2.97	-0.40	-0.21	-0.03	0.14	0.28	0.44	0.64	0.82	0.91
6	-0.01	0.29	0.29	0.22	4.09	-0.44	-0.25	-0.04	0.10	0.29	0.47	0.65	0.74	1.35
7	0.05	0.30	0.29	0.17	3.86	-0.41	-0.25	-0.08	0.10	0.30	0.48	0.67	0.76	1.34
8	0.13	0.31	0.32	0.10	3.79	-0.51	-0.29	-0.07	0.10	0.31	0.47	0.77	0.80	1.41
9	0.28	0.31	0.36	0.26	3.52	-0.56	-0.32	-0.15	0.08	0.30	0.49	0.81	0.90	1.50
10	2.04	0.20	0.34	0.28	2.99	-0.59	-0.34	-0.26	-0.02	0.23	0.40	0.69	0.78	1.25

Panel B: Market Cap Weighted Credit Beta Portfolios

β Sort	Average β	Mean	SD	Skew	Kurt	Min	5%	10%	25%	Median	75%	90%	95%	Max
1	-1.87	0.15	0.29	0.47	3.20	-0.49	-0.27	-0.14	-0.05	0.09	0.31	0.53	0.84	0.85
2	-0.36	0.18	0.30	1.00	4.72	-0.34	-0.29	-0.15	-0.03	0.13	0.34	0.57	0.69	1.23
3	-0.22	0.17	0.30	0.46	3.66	-0.52	-0.31	-0.18	-0.01	0.14	0.40	0.57	0.71	1.12
4	-0.14	0.19	0.31	0.64	4.17	-0.44	-0.30	-0.18	0.01	0.15	0.38	0.54	0.74	1.24
5	-0.07	0.21	0.25	-0.08	3.26	-0.42	-0.23	-0.08	0.06	0.20	0.35	0.57	0.68	0.76
6	-0.01	0.19	0.24	-0.11	3.32	-0.46	-0.27	-0.11	0.03	0.17	0.33	0.47	0.64	0.75
7	0.05	0.21	0.27	0.29	3.03	-0.41	-0.23	-0.12	0.03	0.19	0.40	0.53	0.78	0.90
8	0.13	0.21	0.33	0.21	3.58	-0.60	-0.37	-0.18	0.01	0.21	0.41	0.59	0.71	1.09
9	0.28	0.22	0.33	0.31	3.33	-0.40	-0.37	-0.27	0.00	0.23	0.39	0.66	0.81	1.17
10	2.04	0.26	0.47	1.62	8.49	-0.53	-0.44	-0.19	-0.05	0.18	0.48	0.85	0.94	2.40

Table 11
Average Returns for Cross-Sorted Portfolios

This table presents the average returns for cross-sorted portfolios, formed by sorting independently on credit betas and stock volatility. We use 10 year rolling window regressions for estimating the credit beta. A minimum of 3 years data is required for a valid estimation. The credit beta is estimated at the end of December each year by: $CER_{i,t} = \alpha_{i,t} + \beta_{i,M}\Delta Credit_{t-36} + \epsilon_{i,t}$, where $CER_{i,t} = \sum_{k=t-35}^{t} ER_{i,k}$ is stock $i's$ three year cumulative excess return. $M - 120 \leq t \leq M$. Returns are in decile points.

Panel A: Equal Weighted Average Returns for Cross-Sorted Portfolios

	Volatility				
Credit beta	1	2	3	4	5
1	0.332	0.291	0.294	0.245	0.170
2	0.278	0.290	0.298	0.280	0.227
3	0.270	0.297	0.297	0.306	0.223
4	0.277	0.308	0.317	0.336	0.235
5	0.288	0.303	0.303	0.249	0.107

Panel B: Market Cap Weighted Average Returns for Cross-Sorted Portfolios

	Volatility				
Credit beta	1	2	3	4	5
1	0.225	0.164	0.209	0.144	0.055
2	0.173	0.202	0.215	0.187	0.124
3	0.207	0.221	0.209	0.172	0.194
4	0.199	0.223	0.221	0.273	0.222
5	0.203	0.244	0.243	0.226	0.103

Table 12
Excess Returns on Credit Beta Portfolios

This table presents the excess returns of the credit beta portfolios using the Fama & French three factor model. We use 10 year rolling window regressions for estimating the credit betas. A minimum of 3 years data is required for a valid estimation. The credit beta is estimated at the end of December each year by: $CER_{i,t} = \alpha_{i,t} + \beta_{i,M}\Delta Credit_{t-36} + \epsilon_{i,t}$, where $CER_{i,t} = \sum_{k=t-35}^{t} ER_{i,k}$ is stock $i's$ three year cumulative excess return. $M - 120 \leq t \leq M$. We present results for both equal weighted (EW) and market weighted (MW) portfolios.

Sort Variable	Coefficient	1	2	3	4	5	6	7	8	9	10
$\beta_{i,M}$											
	Average Excess Return (EW)	0.22	0.28	0.29	0.30	0.30	0.29	0.30	0.31	0.31	0.20
	Mkt - rf	1.14***	1.06***	0.98***	0.93***	0.91***	0.91***	0.89***	0.93***	0.97***	1.09***
		(28.06)	(36.81)	(47.59)	(56.65)	(64.37)	(64.87)	(63.71)	(63.34)	(47.31)	(35.45)
	SMB	1.07***	0.80***	0.65***	0.59***	0.57***	0.60***	0.67***	0.78***	1.01***	1.24***
		(18.21)	(19.10)	(21.63)	(24.77)	(27.67)	(29.79)	(33.09)	(36.93)	(34.04)	(27.76)
	HML	0.32***	0.45***	0.45***	0.45***	0.43***	0.40***	0.36***	0.30***	0.20***	0.15***
		(5.08)	(10.20)	(14.09)	(18.09)	(19.62)	(18.93)	(16.70)	(13.60)	(6.53)	(3.13)
	α	-0.35**	-0.01	0.09	0.07	0.14**	0.08	0.03	0.01	-0.14	-0.52***
		(-1.99)	(-0.12)	(1.05)	(1.04)	(2.18)	(1.36)	(0.54)	(0.20)	(-1.59)	(-3.84)
	Adjusted R^2	0.74	0.80	0.87	0.90	0.92	0.92	0.93	0.93	0.90	0.84
	N	527	527	527	527	527	527	527	527	527	527
	Average Excess Return (MW)	0.15	0.18	0.17	0.19	0.21	0.19	0.21	0.21	0.22	0.26
	Mkt - rf	1.32***	1.21***	1.04***	1.01***	0.95***	0.95***	0.96***	0.95***	1.04***	1.18***
		(35.09)	(37.46)	(48.04)	(56.06)	(59.42)	(60.51)	(55.69)	(44.69)	(39.50)	(32.35)
	SMB	0.33***	0.03	-0.18***	-0.15***	-0.14***	-0.10***	-0.09***	0.12***	0.32***	0.73***
		(6.02)	(0.68)	(-5.74)	(-5.78)	(-6.08)	(-4.20)	(-3.58)	(3.89)	(8.33)	(13.76)
	HML	-0.01	0.10**	0.15***	0.22***	0.12***	0.14***	0.06**	0.03	-0.14***	-0.19***
		(-0.21)	(2.00)	(4.68)	(8.19)	(4.88)	(5.87)	(2.34)	(0.83)	(-3.45)	(-3.41)
	α	-0.28*	0.08	0.19**	0.01	-0.06	-0.07	-0.09	0.02	0.04	-0.31*
		(-1.72)	(0.55)	(2.04)	(0.07)	(-0.79)	(-1.06)	(-1.16)	(0.18)	(0.36)	(-1.92)
	Adjusted R^2	0.75	0.75	0.82	0.86	0.88	0.88	0.87	0.82	0.81	0.77
	N	527	527	527	527	527	527	527	527	527	527

Appendix

Table A

This table presents the regression results for credit-beta portfolios on the Fama-French three factor model. We use 10 year rolling window regressions for estimating the credit betas. A minimum of 3 years data is required for a valid estimation. The credit beta is estimated at the end of December each year by: $CER_{i,t} = \alpha_{i,t} + \beta_{i,M}\Delta Credit_{t-36} + \epsilon_{i,t}$, where $CER_{i,t} = \sum_{k=t-35}^{t} ER_{i,k}$ is stock $i's$ three year cumulative excess return. $M - 120 \leq t \leq M$. We present results for both equal weighted (EW) and market weighted (MW) portfolios.

Sort Variable	Coefficient	1	2	3	4	5	6	7	8	9	10
β^{Cont}		-13.50	-5.40	-3.01	-1.52	-0.36	0.68	1.80	3.20	5.39	12.99
	Average Excess Return										
	Mkt - rf	1.16***	1.07***	1.00***	0.93***	0.91***	0.89***	0.89***	0.91***	0.97***	1.05***
		(30.89)	(44.85)	(52.19)	(56.52)	(62.46)	(64.54)	(61.21)	(55.67)	(44.60)	(30.66)
	SMB	1.27***	0.98***	0.79***	0.72***	0.63***	0.65***	0.68***	0.75***	0.86***	1.08***
		(23.19)	(28.51)	(28.65)	(30.20)	(30.09)	(32.54)	(32.59)	(31.41)	(27.44)	(21.80)
	HML	0.16***	0.32***	0.36***	0.39***	0.39***	0.38***	0.33***	0.31***	0.23***	0.10*
		(2.85)	(8.90)	(12.48)	(15.35)	(17.44)	(17.83)	(14.80)	(12.53)	(6.85)	(1.95)
	α	-0.62***	-0.30***	-0.13	-0.05	0.03	0.12**	0.09	0.07	-0.07	-0.56***
		(-3.78)	(-2.88)	(-1.60)	(-0.69)	(0.48)	(1.99)	(1.45)	(0.98)	(-0.74)	(-3.70)
	R^2	0.79	0.88	0.90	0.91	0.92	0.93	0.92	0.91	0.87	0.79
	N	527	527	527	527	527	527	527	527	527	527
	Average Excess Return (MW)										
	Mkt - rf	1.34***	1.25***	1.10***	1.00***	0.97***	0.91***	0.95***	0.99***	1.04***	1.20***
		(41.27)	(45.49)	(52.87)	(56.65)	(68.51)	(58.38)	(65.77)	(56.48)	(43.12)	(35.97)
	SMB	0.71***	0.30***	0.10***	-0.02	-0.07***	-0.09***	-0.12***	0.02	0.19***	0.48***
		(15.15)	(7.52)	(3.20)	(-0.88)	(-3.29)	(-3.86)	(-5.74)	(0.92)	(5.41)	(9.98)
	HML	-0.08	0.10**	0.11***	0.17***	0.12***	0.16***	0.03	-0.01	-0.16***	-0.33***
		(-1.63)	(2.25)	(3.47)	(6.28)	(5.33)	(6.84)	(1.20)	(-0.49)	(-4.24)	(-6.40)
	α	-0.31**	-0.26**	-0.05	-0.14*	-0.11*	-0.05	0.11*	0.11	0.10	-0.02
		(-2.19)	(-2.16)	(-0.58)	(-1.82)	(-1.73)	(-0.70)	(1.68)	(1.43)	(0.98)	(-0.15)
	R^2	0.83	0.83	0.86	0.87	0.91	0.87	0.90	0.88	0.82	0.79
	N	527	527	527	527	527	527	527	527	527	527
$\beta^{Lag\ 1M}$											
	Average Excess Return										
	Mkt - rf	1.17***	1.06***	0.99***	0.93***	0.92***	0.89***	0.90***	0.91***	0.96***	1.04***
		(31.08)	(41.30)	(53.74)	(59.47)	(65.87)	(64.84)	(62.11)	(55.84)	(43.05)	(30.01)
	SMB	1.19***	0.95***	0.79***	0.72***	0.63***	0.66***	0.69***	0.76***	0.90***	1.13***
		(21.82)	(25.63)	(29.34)	(31.73)	(31.12)	(33.25)	(33.01)	(32.33)	(27.73)	(22.44)
	HML	0.16***	0.34***	0.39***	0.38***	0.38***	0.36***	0.32***	0.32***	0.23***	0.09*
		(2.86)	(8.65)	(13.77)	(15.89)	(17.73)	(17.10)	(14.43)	(12.65)	(6.82)	(1.74)
	α	-0.68***	-0.29***	-0.20**	-0.01	0.04	0.07	0.08	0.12	-0.07	-0.47***
		(-4.12)	(-2.60)	(-2.45)	(-0.17)	(0.61)	(1.13)	(1.26)	(1.62)	(-0.74)	(-3.09)
	R^2	0.79	0.85	0.90	0.92	0.93	0.93	0.92	0.91	0.87	0.79
	N	527	527	527	527	527	527	527	527	527	527

	Average Excess Return (MW)										
	Mkt - rf	1.32***	1.22***	1.08***	1.02***	0.96***	0.92***	0.96***	1.01***	1.03***	1.17***
		(38.99)	(41.67)	(50.29)	(62.06)	(70.27)	(64.18)	(59.27)	(53.46)	(40.45)	(34.38)
	SMB	0.66***	0.22***	0.04	-0.02	-0.07***	-0.11***	-0.02	0.02	0.22***	0.50***
		(13.50)	(5.24)	(1.43)	(-0.94)	(-3.52)	(-5.36)	(-0.86)	(0.62)	(5.95)	(10.03)
	HML	-0.05	0.14***	0.15***	0.17***	0.14***	0.06***	0.06**	-0.00	-0.13***	-0.30***
		(-0.95)	(3.14)	(4.48)	(6.92)	(6.53)	(2.83)	(2.27)	(-0.04)	(-3.24)	(-5.72)
	α	-0.42***	-0.27**	-0.17*	-0.17**	-0.02	0.03	0.07	0.17**	0.06	0.05
		(-2.86)	(-2.08)	(-1.84)	(-2.31)	(-0.40)	(0.40)	(1.04)	(2.06)	(0.58)	(0.31)
	R^2	0.81	0.80	0.84	0.89	0.91	0.89	0.88	0.86	0.80	0.78
	N	527	527	527	527	527	527	527	527	527	527
$\beta^{Lag\ 12M}$											
	Average Excess Return										
	Mkt - rf	1.16***	1.05***	0.97***	0.95***	0.91***	0.89***	0.88***	0.92***	0.97***	1.07***
		(31.27)	(38.79)	(49.87)	(57.27)	(67.02)	(62.77)	(62.95)	(55.60)	(41.22)	(27.92)
	SMB	1.31***	1.01***	0.86***	0.75***	0.66***	0.62***	0.61***	0.67***	0.81***	1.04***
		(24.39)	(25.82)	(30.53)	(31.20)	(33.30)	(30.24)	(30.10)	(28.06)	(23.80)	(18.74)
	HML	0.18***	0.35***	0.37***	0.42***	0.42***	0.41***	0.34***	0.31***	0.21***	0.02
		(3.23)	(8.53)	(12.22)	(16.60)	(20.12)	(18.61)	(15.67)	(12.18)	(5.96)	(0.41)
	α	-0.52***	-0.19	-0.01	-0.01	0.07	0.07	0.13**	0.01	-0.09	-0.59***
		(-3.20)	(-1.65)	(-0.12)	(-0.19)	(1.17)	(1.09)	(2.07)	(0.16)	(-0.89)	(-3.51)
	R^2	0.80	0.84	0.89	0.91	0.93	0.92	0.92	0.90	0.85	0.75
	N	527	527	527	527	527	527	527	527	527	527
	Average Excess Return (MW)										
	Mkt - rf	1.34***	1.16***	1.06***	1.01***	0.98***	0.94***	0.95***	1.00***	1.05***	1.18***
		(36.56)	(39.96)	(48.10)	(55.56)	(60.69)	(67.18)	(60.16)	(54.74)	(39.86)	(34.42)
	SMB	0.86***	0.40***	0.23***	0.10***	0.00	-0.09***	-0.09***	-0.05*	0.03	0.38***
		(16.28)	(9.61)	(7.20)	(3.63)	(0.08)	(-4.36)	(-3.77)	(-1.90)	(0.74)	(7.74)
	HML	-0.07	0.02	0.13***	0.09***	0.13***	0.14***	0.10***	-0.01	-0.10**	-0.33***
		(-1.33)	(0.43)	(3.84)	(3.10)	(5.44)	(6.77)	(4.01)	(-0.25)	(-2.37)	(-6.20)
	α	-0.34**	0.05	0.03	-0.01	-0.11	0.06	0.04	0.04	-0.06	-0.04
		(-2.13)	(0.42)	(0.30)	(-0.11)	(-1.61)	(0.96)	(0.51)	(0.53)	(-0.54)	(-0.28)
	R^2	0.81	0.80	0.84	0.87	0.89	0.90	0.88	0.87	0.78	0.77
	N	527	527	527	527	527	527	527	527	527	527
$\beta^{Lag\ 24M}$											
	Average Excess Return										
	Mkt - rf	1.13***	1.07***	0.99***	0.93***	0.92***	0.91***	0.91***	0.90***	0.95***	1.07***
		(31.13)	(39.50)	(46.29)	(53.60)	(58.28)	(65.80)	(64.00)	(54.22)	(43.53)	(29.42)
	SMB	1.15***	0.86***	0.71***	0.65***	0.64***	0.63***	0.68***	0.78***	0.97***	1.14***
		(21.96)	(21.97)	(22.99)	(25.62)	(28.14)	(31.71)	(33.33)	(32.27)	(30.55)	(21.53)
	HML	0.45***	0.53***	0.48***	0.47***	0.46***	0.40***	0.31***	0.19***	0.08**	-0.07
		(8.06)	(12.92)	(14.60)	(17.52)	(18.99)	(18.85)	(14.24)	(7.58)	(2.24)	(-1.22)
	α	-0.54***	-0.11	0.02	0.08	0.08	0.06	0.09	0.01	-0.02	-0.49***
		(-3.41)	(-0.90)	(0.27)	(1.06)	(1.12)	(0.98)	(1.40)	(0.19)	(-0.18)	(-3.08)
	R^2	0.78	0.83	0.86	0.89	0.91	0.93	0.93	0.91	0.88	0.78
	N	527	527	527	527	527	527	527	527	527	527

	Average Excess Return (MW)										
	Mkt - rf	1.30***	1.16***	1.09***	1.00***	0.99***	0.98***	0.96***	0.99***	1.02***	1.22***
		(35.30)	(38.17)	(44.11)	(52.39)	(64.29)	(68.71)	(67.06)	(49.46)	(35.26)	(34.76)
	SMB	0.54***	0.08*	-0.08**	-0.08***	-0.09***	-0.08***	-0.05***	0.06**	0.30***	0.48***
		(10.16)	(1.73)	(-2.16)	(-2.99)	(-3.90)	(-3.64)	(-2.61)	(2.04)	(7.17)	(9.43)
	HML	0.22***	0.36***	0.26***	0.30***	0.19***	0.16***	-0.01	-0.20***	-0.35***	-0.47***
		(3.98)	(7.74)	(6.71)	(10.41)	(8.01)	(7.32)	(-0.51)	(-6.70)	(-7.99)	(-8.77)
	α	-0.30*	-0.01	0.14	-0.01	-0.07	-0.11*	0.05	0.01	0.17	-0.17
		(-1.84)	(-0.04)	(1.29)	(-0.17)	(-1.06)	(-1.71)	(0.74)	(0.15)	(1.36)	(-1.09)
	R^2	0.76	0.75	0.80	0.84	0.89	0.91	0.91	0.86	0.78	0.79
	N	527	527	527	527	527	527	527	527	527	527
$\beta^{Lag\ 36M}$											
	Average Excess Return										
	Mkt - rf	1.14***	1.06***	0.98***	0.93***	0.91***	0.91***	0.89***	0.93***	0.97***	1.09***
		(28.06)	(36.81)	(47.59)	(56.65)	(64.37)	(64.87)	(63.71)	(63.34)	(47.31)	(35.45)
	SMB	1.07***	0.80***	0.65***	0.59***	0.57***	0.60***	0.67***	0.78***	1.01***	1.24***
		(18.21)	(19.10)	(21.63)	(24.77)	(27.67)	(29.79)	(33.09)	(36.93)	(34.04)	(27.76)
	HML	0.32***	0.45***	0.45***	0.45***	0.43***	0.40***	0.36***	0.30***	0.20***	0.15***
		(5.08)	(10.20)	(14.09)	(18.09)	(19.62)	(18.93)	(16.70)	(13.60)	(6.53)	(3.13)
	α	-0.35**	-0.01	0.09	0.07	0.14**	0.08	0.03	0.01	-0.14	-0.52***
		(-1.99)	(-0.12)	(1.05)	(1.04)	(2.18)	(1.36)	(0.54)	(0.20)	(-1.59)	(-3.84)
	R^2	0.74	0.80	0.87	0.90	0.92	0.92	0.93	0.93	0.90	0.84
	N	527	527	527	527	527	527	527	527	527	527
	Average Excess Return (MW)										
	Mkt - rf	1.32***	1.21***	1.04***	1.01***	0.95***	0.95***	0.96***	0.95***	1.04***	1.18***
		(35.09)	(37.46)	(48.04)	(56.06)	(59.42)	(60.51)	(55.69)	(44.69)	(39.50)	(32.35)
	SMB	0.33***	0.03	-0.18***	-0.15***	-0.14***	-0.10***	-0.09***	0.12***	0.32***	0.73***
		(6.02)	(0.68)	(-5.74)	(-5.78)	(-6.08)	(-4.20)	(-3.58)	(3.89)	(8.33)	(13.76)
	HML	-0.01	0.10**	0.15***	0.22***	0.12***	0.14***	0.06**	0.03	-0.14***	-0.19***
		(-0.21)	(2.00)	(4.68)	(8.19)	(4.88)	(5.87)	(2.34)	(0.83)	(-3.45)	(-3.41)
	α	-0.28*	0.08	0.19**	0.01	-0.06	-0.07	-0.09	0.02	0.04	-0.31*
		(-1.72)	(0.55)	(2.04)	(0.07)	(-0.79)	(-1.06)	(-1.16)	(0.18)	(0.36)	(-1.92)
	R^2	0.75	0.75	0.82	0.86	0.88	0.88	0.87	0.82	0.81	0.77
	N	527	527	527	527	527	527	527	527	527	527