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Q, investment, and the financial cycle

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Q, investment, and the financial cycle

Fabio Verona*

16 July 2017

Abstract

The empirical performance of the Q theory of investment can be significantly improved by simultaneously considering the time- and the frequency-varying features of the investment-Q relationship. Using continuous wavelet tools, I assess the investment-Q sensitivity at different frequencies and its evolution over time, as well as the interaction of the financial cycle with the Q theory. The results show that there is a positive, stable medium-to-long-run relationship between investment and Q that begins after a positive, stable long-run relationship between credit and Q materializes. In such case, credit leads and slowly fuels the stock price boom.

Keywords: Tobin's Q, investment, financial cycle, time-frequency estimation, continuous wavelets

JEL codes: C49, E22, G31

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1 Introduction

The Tobin's Q theory of investment (Tobin, 1969) predicts that business investment should positively depend on Q only, where Q is usually defined as the ratio of the fundamental market value of a firm (the stock price, assuming that stock markets are efficient) relative to the replacement cost of the firm's physical assets (the market value of the firm's capital stock). Despite the attractiveness of its simplicity and soundness of its theoretical underpinnings, empirical tests have largely rejected the Q theory. Indeed, empirical studies typically find the effect of Q on investment to be rather weak, not always statistically significant, and often dominated by direct effects of other variables such as cash flow or sales (see *e.g.* Chirinko, 1993, Caballero et al., 1995 and Bond and Van Reenen, 2007).

A common explanation for this empirical failure is that Q has been poorly measured. The numerator of Q could reflect, for instance, bubbles or fads in the stock market. The denominator of Q could measure something other than the value of the existing physical capital stock. If, say, investors incorporate intangible assets into their valuation of a firm, the company capital stock market value could markedly differ from the value of the firm's tangible assets alone (Brynjolfsson et al., 2002). In recent years, researchers have proposed several alternative proxies for Q (see sub-section 2.1.1 for a review). For instance, Hall (2001) notes that intangible capital (such as brand names, patents, copyrights, innovative products, corporate culture, and human capital) represents an increasingly important part of the total stock of capital of modern economies. Thus, ignoring intangible capital may lead to poor measurement of both investment and Q.

Motivated by this observation, Peters and Taylor (2017) propose a method to measure intangible capital accumulation by firms, which affects both the numerator and the denominator of investment rate, as well as the denominator of Q. They then show that the fit of the investment equation using these new measures for Q and investment (named "total Q" and "total investment") is remarkably better than the fit with the traditional measures of Q and investment. As conjectured by Peters and Taylor (2017) and empirically shown by Kilponen and Verona (2016), much of this improved performance can be attributed to how well total Q captures the effect on total investment at different frequencies – especially at business-cycle frequencies and over the long run. These results are encouraging and suggest that the Q theory works well when good measures of investment and Q are used in the investment regression and the frequency

dependence between variables is taken into account. Actually, over the years several authors have argued that Q (and possibly other variables) may affect investment at different frequencies (see *e.g.* Engle and Foley, 1975, Lettau and Ludvigson, 2002, Alti, 2003, Almeida et al., 2004 and Abel and Eberly, 2012).

Besides the frequency dependence between investment and Q, empirical evidence has shown that the investment-Q sensitivity is time-varying and, more importantly, unstable over time. For instance, Gallegati and Ramsey (2013b) estimate (by OLS) the investment equation over different sub-samples and find that the fit of the regressions and the estimated investment-Q sensitivities differ according to the estimation period. For instance, they find that the investment-Q sensitivity has the expected positive sign in some periods of time while a negative sign in other periods.

In the light of the empirical evidence, a reasonable testing of the Q theory should therefore take into account the variation over time of the investment-Q sensitivity *and* the frequency dependence between investment and Q. Motivated by this, the first contribution of this paper is to revisit the empirical performance of the Q theory of investment in the time-frequency domain, *i.e.* in a framework where both the time and the frequency domain are simultaneously taken into account. I do so by using the continuous wavelet tools (CWT) developed by Aguiar-Conraria et al. (2017). These tools allow me to estimate the investment-Q sensitivity over time and across frequencies so that I can analyze and determine those periods of time and frequencies at which the Q theory works well.

The second contribution of the paper is to analyze the time-and-frequency-varying role that credit has played as driver of macroeconomic fluctuations – most notably investment and asset prices (*i.e.* Q) booms and busts. The financial crisis of 2008 and 2009 has reignited interest in understanding the crucial role of credit (and financial markets more generally) in driving real business cycle fluctuations. Credit has often alternated between booms (periods of rapid growth) and busts (periods of stagnation or significant decline). These booms and busts tend to be followed by similar fluctuations in macro (GDP, investment) and financial (asset prices) variables. The financial innovation and regulatory easing that started in the US in the 1980s led to a 30-year credit boom that increased the quantity and the availability of credit for all borrowers. This period of unprecedented credit expansion ended with the Great Recession, bringing to an end the era of outlandish borrowing. By using the CWT I can also analyze the time-and-frequency varying role played by the credit/financial cycle in the context of the Q theory of investment.

Using the traditional measures of Q (based on the stock market) and investment (that only accounts for physical capital, *i.e.* tangible assets), the main finding of this paper is that there is indeed a positive, stable medium-to-long-run relationship between investment and Q that begins a few years after a similar positive, stable long-run relationship between credit (bank loans) and Q materializes. So these findings suggest that the Q theory works well in the long run (8- to 20-year cycles) and for periods when growth in asset prices (*i.e.* Q) are slowly fueled by credit.[1]

The rest of the paper is organized as follows. Section 2 briefly reviews the two strands of literature on which this paper builds, *i.e.* the Q theory of investment and the use of wavelet tools in analyzing the time-frequency relationship between macro and financial variables. The data is described in section 3. The Q theory is tested in the time domain and in the time-frequency domain in section 4. Section 5 concludes.

2 Motivation, contribution, and related literature

This paper is motivated by the empirical failures of the Q theory and recent progress in application of wavelet tools to estimation of a parametric function, such as the investment equation, in the time-frequency domain. I believe (and show) that wavelet tools can partially help in solving problems related to the empirical failures of the Q theory.[2] I start the analysis with a brief overview of these two strands of the literature.

[1] In the online appendix, I document the robustness of these results i) using the Peters and Taylor (2017) proxies for Q and investment that also account for intangible assets, and ii) for the Q theory of housing investment, as first proposed and tested by Takala and Tuomala (1990).

[2] Model misspecification is the most common theoretical reason for the failure of the Q theory. Recall that, according to the Q theory, investment should be an increasing function of marginal Q, while from the data one can (imprecisely) measure average Q. Hayashi (1982) shows that marginal and average Q are the same for a competitive firm with constant returns to scale (both in the production function and in the adjustment cost function). However, when these conditions are not met, Q is no longer a sufficient statistic for investment and the Q theory fails (see *e.g.* Gomes, 2001, Cooper and Ejarque, 2003, Alti, 2003, Moyen, 2004 and Abel and Eberly, 2011). At the micro level, for instance, returns to scale are likely to be decreasing and adjustment costs are likely to be non-convex, so the theory is expected to fail. Recently, researchers have proposed models with better microfoundations, *e.g.* with lumpy or irreversible investment (see *e.g.* Veracierto, 2002, Cooper and Haltiwanger, 2006, Khan and Thomas, 2008, Verona, 2014a,b and Bustamante, 2016).

2.1 The empirical failure of the Q theory of investment: the quest for better proxies and estimators

2.1.1 Better proxies

Finding better observable proxies for Q has long been recognized as crucial for improving the fit of the investment equation. Besides the above-mentioned measure that includes intangible capital and investment (Hall, 2001 and Peters and Taylor, 2017), researchers have proposed other proxies for Q. McGrattan and Prescott (2005) show that a measure of Q that takes into account changes in tax and regulatory policy, as well as intangible capital, mimics fairly well trends in the market values of US and UK firms. Merz and Yashiv (2007) augment a standard Q model with labor adjustment costs and show that labor market frictions are crucially important for the model's empirical relevance as both optimal hiring and investment decisions determine firm's profits and, consequently, firm's market value. Philippon (2009) constructs an alternative market-based measure of Q using corporate and government bond prices instead of equity prices. The new variable (named "bond Q") seems to be a better proxy for Q in three respects: the fit of the regression is much higher than using the standard equity Q measure, the implied investment-Q sensitivity is higher (hence the underlying investment adjustment cost parameter is lower), and the cash flow effect disappears once bond Q is included in the regression. Finally, other measures of Q have been computed using analyst forecasts rather than the firm's market value (Cummins et al., 2006), and an option pricing framework (Celil and Chi, 2016). In this paper we mainly focus on the standard measures of Q and investment, but we report the results using alternative measures in the online appendix.

2.1.2 Better estimators

Another explanation for empirical failures is that OLS regressions produce downward-biased estimates of the coefficient on Q. This explanation has generated several studies. Erickson and Whited (2000) show that their measurement error-consistent GMM estimator of the coefficient on Q is much larger than with the OLS estimator. Erickson et al. (2014) estimate the investment model using cumulant estimator and show that it outperforms the moment estimator proposed by Erickson and Whited (2002).

Moreover, stability of regression coefficients is a key assumption underlying the classical linear regression

model, but it is unlikely to be realistic when a given relationship is estimated over a long sample period. When modeling unstable relationships, ignoring the presence of possible structural changes can lead to incorrect and unreliable estimation results. In fact, Gallegati and Ramsey (2013b) find that the significance of the investment-Q sensitivity and the degree of fit of the investment regression change significantly depending to the estimation periods (detected using the Bai and Perron, 1998, 2003 sequential testing procedure). Similarly, McLean and Zhao (2014) show that the investment-Q sensitivity time-varies with the business cycle, with sensitivity highest during expansions.[3] Hence, the poor performance of the linear Q model could also arise from violation of the parameter constancy assumption. The CWT method used in this paper (and described in the next sub-section) allows indeed to take into consideration the time-varying features of the investment-Q sensitivity.

2.2 Wavelets analysis

Wavelets have long been very popular in many fields such as geophysics, engineering, medicine and biomedical engineering, as well as for real-life applications (like the FBI algorithm for fingerprint data compression). Notably, Yves Meyer, a French mathematician, received the 2017 Abel Prize "for his pivotal role in the development of the mathematical theory of wavelets".[4] In what follows we give a brief overview of the still scarce, but fast growing, literature on wavelets applications in economics and finance.

2.2.1 Recent contributions in macro-finance

The early economics papers using wavelets rely on the discrete wavelet transform (DWT).[5] Recent studies using the continuous wavelet transform (CWT) have become more common, with CWT fast becoming a popular tool in econometric analysis. The most common argument for using the CWT is the possibility of assessing *simultaneously* how variables are related at different frequencies and how these relationships

[3] These business cycle findings are similar to those obtained using macroeconomic models with the financial accelerator mechanism *à la* Kiyotaki and Moore (1997) and Bernanke et al. (1999). Funke (1990) and Holmes (2010) also analyze the structural stability of the investment-Q relationship. More generally, Sala (2015) and Caraiani (2015) estimate small-scale DSGE models in the frequency and time-frequency domain, respectively, and find that most structural parameters exhibit a (time-)frequency-dependent behavior.

[4] The Abel prize is awarded for outstanding scientific work in the field of mathematics and is considered to be the Nobel Prize in mathematics.

[5] The pioneering works are Ramsey and Lampart (1998a,b) and Ramsey (2002). Some recent studies using the DWT include Rua (2011), Gallegati et al. (2011), Caraiani (2015), Crowley and Hughes Hallett (2015), and Faria and Verona (2016, 2017).

change over time. CWT analysis is also well suited to study the interaction between variables (macro and financial) and cycles (business and credit) that fluctuate and operate at different frequencies. For instance, Verona (2016) shows that the credit/financial cycle operates at lower frequencies than the business cycle.

Three recent papers deserve special mention as they are closely related to this work: Gallegati and Ramsey (2013a), Kilponen and Verona (2016) and Aguiar-Conraria et al. (2017).[6] Using CWT tools, Gallegati and Ramsey (2013a) first analyze the correlation between the traditional measure of investment and two measures of Q (equity Q and bond Q). They do not however estimate the intensity of the investment-Q relationship and if, and eventually how, it changes when controlling for *e.g.* cash flow.[7] Then Gallegati and Ramsey (2013a) apply (similar to Kilponen and Verona, 2016) a maximal overlap DWT (MODWT) to decompose the variables into their different frequency components to OLS-estimate a sequence of investment regressions. The shortcoming of the MODWT approach is that the coefficients in each frequency band are fixed over the sample, so it is not possible to analyze the time-varying dynamics of the investment-Q sensitivity. Furthermore, Gallegati and Ramsey (2013a)

The CWT tools developed by Aguiar-Conraria et al. (2017) allow to overcome these problems, as they make it possible to estimate an equation relating two (or more) variables (in that case, a Taylor rule relating the nominal interest rate with the inflation rate and the output gap) in the time-frequency domain. Namely, these tools facilitate assessment of the intensity, significance, sign, and synchronization of the co-movements of investment, Q and credit. Using these tools I estimate the investment-Q sensitivity (also after controlling for cash flow) in the time-frequency domain.

The next subsection briefly introduces the CWT. The aim here is to provide the reader with some basic definitions and an intuition of the underlying concepts. For more information, Crowley (2007) and Aguiar-Conraria and Soares (2014) provide excellent reviews of the theory and of economic and financial applications of DWT and CWT, respectively.

[6] Other contributions using CWT analysis include Aguiar-Conraria et al. (2008), Crowley and Mayes (2008), Rua and Nunes (2009), Rua (2010, 2012), Aguiar-Conraria and Soares (2011), Aguiar-Conraria et al. (2012, 2013), Caraiani (2012), Gallegati and Ramsey (2014), Ko and Lee (2015), Marczak and Gomez (2015), and Verona (2016).

[7] As widely emphasized in the investment literature (see *e.g.* Bond and Van Reenen, 2007), the significance and explanatory power of Q are often found to be rather weak when other variables (such as sales and cash flow) are added to the econometric model. So controlling for *e.g.* cash flow is crucial as it allows to check whether it drives Q out or not.

2.2.2 CWT: basic concepts

A wavelet $\psi(t)$ is a function of finite length which oscillates around the $t-$axis. It loses power as it moves away from the center. The name wavelet originates from the admissibility condition, which requires the mother wavelet to be of finite support (small) and of oscillatory (wavy) behavior, hence wavelet (small wave).

Let $x(t)$ be a time series. The continuous wavelet transform of $x(t)$ with respect to a given mother wavelet ψ can be written as

$$W_x(\tau, s) = \frac{1}{\sqrt{s}} \int_{-\infty}^{+\infty} x(t) \overline{\psi}\left(\frac{t-\tau}{s}\right) dt \ ,$$

where the bar denotes the complex conjugate, and τ and s are the two control parameters of the CWT. The location parameter τ determines the position of the wavelet along the $t-$axis, and the scale parameter s defines how the mother wavelet is stretched. Scale is inversely related to frequency. A lower (higher) scale means a more (less) compressed wavelet, which is thus able to detect higher (lower) frequencies of the time series.

The most commonly used mother wavelet in economic applications – and the one used here – is the Morlet wavelet $\psi_{\omega_0}(t) = \pi^{-\frac{1}{4}} e^{i\omega_o t} e^{-\frac{t^2}{2}}$, with $\omega_0 = 6$. This specific choice yields a simple relation between scale s and frequency f, with $f \approx 1/s$, and also implies an optimal joint time-frequency resolution.

The wavelet power spectrum of $x(t)$ is defined as $(WPS)_x(\tau, s) = \mid W_x(\tau, s) \mid^2$, and measures the local variance distribution of the time series $x(t)$ around each time and scale/frequency.

Given two time series $x(t)$ and $y(t)$, the cross-wavelet transform of x and y is defined as $W_{xy}(\tau, s) = W_x(\tau, s)\overline{W_y}(\tau, s)$, where $W_x(\tau, s)$ and $W_y(\tau, s)$ are the wavelet transforms of x and y, respectively. The absolute value of $W_{xy}(\tau, s)$ is usually referred to as the cross-wavelet power and captures the local covariance between the two series in the time-frequency space. The wavelet squared coherence is given by

$$R^2(\tau, s) = \frac{\mid S\left(s^{-1} W_{xy}(\tau, s)\right) \mid^2}{S\left(s^{-1} \mid W_x(\tau, s) \mid^2\right) S\left(s^{-1} \mid W_y(\tau, s) \mid^2\right)} \ ,$$

where S denotes a smoothing operator in both time and scale (without smoothing the wavelet coherence would be always equal to one, as in the Fourier analysis). Wavelet squared coherence measures the strength

of the relationship between two variables around each moment in time and for each frequency. It can thus be considered a direct measure of the local correlation between two time series in the time-frequency space. The $R^2(\tau, s)$ is between 0 and 1, with a high (low) value indicating a strong (weak) co-movement.

The wavelet gain of $y(t)$ over $x(t)$ is defined as

$$G_{yx}(\tau, s) = \frac{\mid S\left(s^{-1} W_{xy}(\tau, s)\right) \mid}{S\left(s^{-1} \mid W_x(\tau, s) \mid^2\right)} \ .$$

The gain can be interpreted as the modulus of the regression coefficient in the regression of y on x at each time and frequency.

Finally, the wavelet phase-difference provides information about the lead-lag relationship between the two series (hence, the sign of the wavelet gain) as a function of time and frequency. It is given by

$$\phi_{xy}(\tau, s) = \arctan \frac{\Im\left[W_{xy}(\tau, s)\right]}{\Re\left[W_{xy}(\tau, s)\right]} \ ,$$

where $\Re$ and $\Im$ are the real and imaginary parts of $W_{xy}(\tau, s)$, respectively and $-\pi < \phi_{xy}(\tau, s) < \pi$. Variables are in phase, *i.e.* they move together, if $-\pi/2 < \phi_{xy}(\tau, s) < \pi/2$, with x leading if $0 < \phi_{xy}(\tau, s) < \pi/2$ and y leading if $-\pi/2 < \phi_{xy} < 0$. Otherwise they are out of phase, *i.e.* negatively correlated, with x leading if $-\pi < \phi_{xy}(\tau, s) < -\pi/2$ and y leading if $\pi/2 < \phi_{xy} < \pi$.

As the CWT at a given point in time uses information of neighboring data points, the values of the wavelet transform at the beginning and end of the sample are always incorrectly computed as the time series are, say, padded with zeros. The region in which the transform suffers from such edge effects, which are larger at lower frequencies, is known as the "cone of influence." Hence, the results should be interpreted carefully in this region of the time–frequency space as they are subject to border distortions.

3 The data

The data come from two sources. For investment rate, Tobin's *Q,* and cash flow, we use the dataset of Philippon (2009), which consists of quarterly aggregate US data from 1953:Q2 to 2007:Q2. For the non-financial corporations bank loans series, we use the dataset of Contessi et al. (2015) for the same sample

period.

Aggregate investment rate IK, $IK \equiv I_t^{phy}/K_{t-1}^{phy}$, is computed as the ratio between corporate fixed private nonresidential investment in equipment and structures (I_t^{phy}) and its replacement cost (K_{t-1}^{phy}). The standard measure of Tobin's Q, Q^e, $Q^e \equiv V_t/K_{t-1}^{phy}$, is defined as the ratio of the value of ownership claims on the firm less the book value of inventories (V_t) to the replacement cost of equipment and structures. As proxies for the financial cycle, we use data for two financial variables: bank loans and cash flow. For the bank-loan series, we use annual growth rate obtained by taking the four-quarter differences of the logarithms of the time series. For cash flow, we use the ratio of corporate profits over GDP.

The top graphs in Figures 1 to 4 show the time series of the variables, together with NBER recessions (gray-shaded areas) and with the sample average value of the variable (black horizontal line). The bottom left graphs and bottom right graphs show the wavelet power spectrums (WPS) and the global wavelet power spectrums (GWPS) of the variables, respectively. The WPS measures the variance of the series at each time-frequency locus and provides a time-frequency characterization of the data. In the power spectrum charts (as well as in the coherence charts in the following sections), time is on the horizontal axis and period cycles (in years) on the vertical axis, hotter colors (yellow and red) correspond to higher volatility/coherence and colder colors (green and blue) to lower volatility/coherence, white lines denote the maxima of the undulations of the WPS (an estimate of the cycle periods), black (gray) contours mark significance at the 5% (10%) level, and black dashed lines denote the cone of influence (region affected by edge effects).[8] The GWPS gives the average wavelet power for each frequency and is obtained by averaging the WPS over all times so that it can be directly compared with classical spectral methods. The time-series correlations between variables are reported in Table 1.

The investment rate is pro-cyclical, exhibiting slow booms followed by quick busts. The temporary increase in the investment rate in the late 1970s and early 1980s is due to i) the introduction of energy-saving technologies in energy-intensive industries (see Alpanda and Peralta-Alva, 2010) as a consequence of the oil price shocks of the 1970s, and ii) capital and knowledge obsolescence as result of the arrival of new information technologies (see Greenwood and Jovanovic, 1999 and Laitner and Stolyarov, 2003). Another notable feature of investment is its boom starting in the mid-1990s, which characterizes the longest US

[8] The results in this paper were obtained using an updated version of the ASToolbox, a wavelet Matlab toolbox available at https://sites.google.com/site/aguiarconraria/joanasoares-wavelets/the-astoolbox. Significance levels were obtained by bootstrapping with 5,000 replications.

expansionary period in the post-World War II era. The boom ends just before the collapse of the dot-com bubble in 2001.

The WPS of investment rate is very high (dark red) throughout the entire sample at frequencies around 16 years (which is consistent with the peak in the GWPS at that frequency). There is also evidence of a second cycle, starting from 1960, at a frequency of about 8 years, which gradually shortens and loses importance until disappearing in 1985. At about the same time, a longer cycle (about 10 years) starts and slowly becomes a 12-year cycle that ends just before the large investment bust at the beginning of 2000.

In addition to saw-tooth movements, Q^e exhibits large and low-frequency swings, moving upward until 1968, then downward to 1982, and upward again until the burst at the beginning of 2000. No strong relationship seems to emerge between Q^e and investment (the sample correlation is 0.29). They diverge between the mid-1970s and the early 1990s, with Tobin's Q being low both in absolute terms and in relation to investment. From the mid-1990s onward, they then co-move and exhibit boom-bust cycles, which is consistent with the rise and collapse of the dot-com bubble. Looking at the WPS, throughout the entire sample the volatility of Q^e occurs mainly at low frequencies (more than 16 years). Starting from 1985, the volatility also increases at somehow higher frequencies, with a second cycle with a period of about 7 years appearing in the last 10 years of the sample.

The bank loans series is also pro-cyclical, with the long drops usually starting before and ending after the corresponding business cycle recession. At the beginning of the sample, bank loans feature three main cycles: one with a period of 4 years, one with an 8-year period, and a longer 20-year period cycle. The first two cycles slowly converge over time, merging at around 1980 and then forming a 6-year cycle. The long cycle gradually shortens over the sample, becoming a 12-year cycle by the end of the sample. Similarly, the GWPS shows that the majority of the variability of bank loans occurs at 6- and 14-years cycles.[9]

Cash flow displays a slow downward trend until 1983 and then an upward trend (interrupted by a large drop between 1997 and 2000) until the end of the sample. Cash flow seems to lead the business cycle, usually peaking a few quarters before the subsequent business cycle recession. The volatility of cash flow occurs mainly at frequencies between 8 and 16 years throughout the entire sample, with the main cycle featuring a period of about 10 years.

[9] All the results in this paper are robust using the amount of bonds issued by non-financial corporations or the sum of bank loans and bonds issued.

Having described the data, I now start the empirical analysis by testing the Q theory of investment both in the time and time-frequency domain.

4 Testing the Q theory of investment

4.1 Time domain: time series analysis

In the literature, the investment rate is usually regressed on Tobin's Q, measured at the end of the previous quarter: $IK_t = \beta_0 + \beta_{Q^e} Q^e_{t-1} + \varepsilon_t$. The OLS estimation results for the full sample period are reported in the third column of Table 2. The standard errors control for autocorrelation in the error terms up to four quarters. Results are as expected and well known: β_{Q^e} is very low and marginally statistically significant (10% level), and Q^e only explains about 10% of the investment variations.

As mentioned in the introduction, the empirical evidence suggests that the investment-Q^e sensitivity is time-varying and unstable over time. To account for this, and following Gallegati and Ramsey (2013b), we first apply the Bai and Perron (1998, 2003) sequential testing procedure to find the structural breaks in the investment-Q relationship, and then re-estimate the investment equation for each sub-sample. The Bai and Perron test identifies four breaks in the investment-Q^e relationship: 1965:Q1, 1977:Q4, 1986:Q2 and 1999:Q3. The last five columns in Table 2 report the OLS sub-sample investment regression results. The findings from the sub-sample regression analysis clearly confirm the existence of a temporal instability in the investment-Q^e relationship, as the estimated coefficients and R^2s differ widely across the periods. In the first and third periods, the results are worse than in the full sample case, as the β_{Q^e} coefficients are no longer statistically significant. In the other periods, the coefficients are statistically significant (at the 1% level) and two to three times larger than in the full sample. The overall fit of the regression is also much better, with adjusted R^2s of 56%, 64% and 91% in the second, fourth, and fifth periods, respectively.

The temporal instability exhibited by the investment-Q^e relationship thus strengthens the case in favor of using an empirical method – such as continuous wavelets – to study the (frequency) relationship between investment and Q^e without losing the information about the time-varying dynamics underlying the investment-Q relationship.

4.2 Time-frequency domain: wavelet analysis

4.2.1 Investment and Q^e

To describe the time-frequency relationships between investment, Q^e and the financial cycle, I present wavelet phase-diagrams and gains for three frequency intervals, namely for cycles of period $1.5 \sim 4$ years (the short end of business cycles, or the "short run"), cycles of period $4 \sim 8$ years (the bulk of traditional business cycle fluctuations, or the "medium run"), and cycles of period $8 \sim 20$ years (capturing the long-run relationship between the variables, or the "long run").

Figure 5 displays the time-frequency relationship between investment and Q^e. The coherence (graph on the top row) shows that the correlation is unstable, but high (red areas) and statistically significant in about 50% of the time-frequency locus. Thus, despite periods in which the correlation is weak (blue areas up to 1985 in the long run, between 1980 and 1997 in the medium run, and from 1985 to 1997 in the short run), there are periods where there is evidence of a strong correlation between these variables. In particular, from 1985 onwards the empirical evidence provide support for the existence of a stable long-run relationship between investment and Tobin's Q.

The wavelet gains are reported in the middle row. Recall that they portray the modulus of the β_{Q^e} coefficient at each time and frequency. As can be seen, the highest β_{Q^e} values are at around 1980 for all frequencies, while they then decrease until the end of the sample, with the short-run coefficient reaching a rather low level.[10] To summarize the results about the magnitude of the investment-Q^e sensitivity, Figure 6 reports the wavelet gains (black line: $1.5 \sim 4$-year gain; red line: $4 \sim 8$-year gain; blue line: $8 \sim 20$-year gain) as well as the results in the time domain (yellow line: OLS regression over the entire sample; green line: OLS sub-sample regression).

Two results here deserve more discussion. First, the investment-Q^e sensitivities in the time-frequency domain are usually larger than in the time domain (even after controlling for structural breaks). This is an improvement on results seen in the literature as this coefficient is closely related with the inverse of the investment adjustment cost parameter. In particular, a common empirical finding that leads to the rejection of the Q theory is that β_{Q^e} is extremely low, so adjustment costs are unreasonably large and not credible

[10] As one would expect, the long-run gain and phase difference display smoother behaviors as they capture the relationship between the long-run (*i.e.* the low-frequency) components of the variables.

as they imply implausibly slow adjustment of the actual capital stock toward its optimal (or desired) level. Wavelet tools thus allow for an improvement with respect to standard time series methods. Even though the wavelet gains decrease toward the end of the sample, the medium- and long-run investment-Q^e sensitivities are anyway twice as large as the β_{Q^e} coefficient estimated over the entire sample. Second, the power in the investment-Q^e relationship has moved from the medium run (4 to 8 years) in the first part of the sample (from 1965 until 1980) to the long run (over 8 years) from 1987 onward. The only exception is the period 1980-1986, when the short-run gain is the highest and negative (according to the phase difference). This result comports with the negative OLS regression coefficient in that sub-sample period.

Finally, when the coherence is statistically significant, the phase differences (graphs in the bottom row) indicate that a) investment and Q^e are usually in phase (the phase difference is usually between $-\pi/2$ and $\pi/2$), which in turn implies that the β_{Q^e} coefficients are usually positive in all frequency bands (*i.e.* there is a positive relationship between investment and Q^e), and b) Q^e leads investment at business cycle frequencies (the phase difference is between $-\pi/2$ and 0 in the frequency bands $1.5 \sim 4$ and $4 \sim 8$ years), while investment leads Q^e in the long run (the phase difference is between 0 and $\pi/2$ in the $8 \sim 20$-year frequency band).

This frequency-dependent lead-lag relationship between investment and Q^e offers a new insight into the Q theory of investment. Recall that Q^e is a forward-looking variable that should capture the expected present discounted value of firm's profits. At traditional business-cycle frequencies ($1.5 \sim 8$ years), Q leads and drives investment decisions. In other words, the higher the firm's current and future profits (*i.e.* Tobin's Q of the firm), the greater the firm's incentive to invest in physical capital. In the long run, however, investment stimulates Q, so the more the firm invests, the more its market value is expected to go up. An endogenous growth model could rationalize this long-run effect, whereby higher investment leads to higher expected future productivity and therefore to higher current and future profits (*i.e.* higher Tobin's Q) and, ultimately, to higher economic growth.

4.2.2 Q^e and the financial cycle

As mentioned above, the time series of Q^e broadly exhibits two upward trends (interrupted by a downward period), a shorter one between 1953 and 1968, and a longer one between 1982 and 2000. The second boom (which includes the dot-com bubble) is of particular interest as its outset roughly coincides with the beginning of the financial liberalization period in the early 1980s. We now use the CWT to check whether – and if so, how – these stock market boom episodes are related to the financial cycle. As proxies for the financial cycle, we use data for two financial variables – bank loans and cash flow – as they are likely to capture different corporate investment decisions. Arguably, we would expect cash flow (profits) to be used to finance short-term investment expenditures such as software and equipment, while credit would be used to finance longer term investments such as buildings or plant facilities.

Recall that the time series correlation between Q^e and bank loans/cash flow is rather low (0.04/0.16), so no clear relationship seems to exist between stock prices and credit/cash flow. Figure 7 reports the coherence between Q^e and bank loans (upper plot) and the phase-difference between them in three frequency intervals (remaining panels). Three distinct patterns, which broadly correspond to the above-mentioned low-frequency movements of Q^e, characterize the time-frequency relationship between Q^e and bank loans. First, there is no evidence of any significant correlation between credit and Q^e at any frequency during the first stock market boom episode. Second, in the downward period between the booms, most of the correlation between these variables is concentrated in the short and medium run. Third, starting from 1975, there is a high, positive, and statistically significant correlation in the $8 \sim 20$- year frequency band, with bank loans leading Q^e. Apparently, credit (in form of bank loans) and booming stock prices reinforced each other, with credit leading and fueling a slow, prolonged stock market boom. This long-run relationship between Q^e and the financial cycle disappears when using cash flow as a proxy for the financial cycle. Figure 8 shows that there is very little empirical evidence supporting a significant long-run contribution of cash flow in either stock price boom episode. Cash flow only plays some role between 1965 and 1975 in the short and medium run, and between 1990 and 2000 at frequencies around 8 years.

Overall, these results provide support for the existence of a medium-to-long run positive relationship between investment and Q. Furthermore, such relationship begins a few years after a similar positive,

stable long-run relationship between credit and Q materializes.[11]

5 Conclusions

The investment literature has long acknowledged the time- *and* frequency-varying dynamics of the investment-Q relationship. However, it has largely dismissed their potential value as possible solution for the empirical failure of the Q theory of investment. In this paper, I have estimated the investment equation using an empirical method – the continuous wavelet transform – that allows to assess simultaneously the relationship of investment and Q at different frequencies and how this relationship changes over time. Using the same tools, I have also analyzed how the financial cycle interacts with the Q theory of investment.

It turns out that the Q theory works quite well at some frequencies and points in time. In particular, there is a positive, stable medium-to-long-run relationship between investment and Q that begins a few years after a similar positive and stable long-run relationship between credit and Q materializes, with credit leading and slowly fueling the stock price boom.

Overall, the results in this paper show that considering both the time- and the frequency-varying features of the investment-Q relationship result in a significantly better empirical performance of the Q theory of investment. They also confirm the usefulness of using the continuous wavelet transform as an econometric tool to analyze economic relationships that feature unstable time and frequency behaviors.

[11] The results are robust using the four-quarter differences of the variables (as done by Philippon, 2009). I further check the robustness of the results by introducing cash flow as an additional regressor into the investment equation using the wavelet multivariate CWT developed by Aguiar-Conraria et al. (2017). While cash flow is clearly an important determinant of investment, so is Q^e. Thus, including cash flow does not drive out Q^e. The coefficient on cash flow is larger in the medium run, so the power in the relationship between investment and cash flow is at medium frequencies. Moreover, regardless of the frequency, the investment-cash-flow sensitivity does not disappear or decline over time, as instead found by *e.g.* Chen and Chen (2012) and Lewellen and Lewellen (2016) using micro-level data.

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	IK	Q^e	bank loans	cash flow
IK	1			
Q^e	0.29	1		
bank loans	0.56	0.04	1	
cash flow	-0.04	0.16	0.37	1

Table 1: Correlation matrix

Notes. This table reports the time-series correlation between the variables. Data for IK, Q^e, and cash flow are from Philippon (2009), and data for bank loans from Contessi et al. (2015); quarterly data, 1953:Q2 to 2007:Q2.

Dependent variable: IK_t							
	sample period	1953:Q2 2007:Q2	1953:Q2 1964:Q4	1965:Q1 1977:Q3	1977:Q4 1986:Q1	1986:Q2 1999:Q2	1999:Q3 2007:Q2
Q^e_{t-1}	β_{Q^e}	0.004*	0.002	0.013***	-0.012	0.010***	0.013***
	s.e.	(0.002)	(0.004)	(0.002)	(0.009)	(0.002)	(0.001)
	$\bar{R}^2$	0.096	0.01	0.56	0.04	0.64	0.91

Table 2: Investment regressions for different samples

Notes. Data for IK and Q^e are from Philippon (2009); quarterly data, 1953:Q2 to 2007:Q2. Estimation of the investment equation over the sub-regions detected by the Bai and Perron (1998, 2003) sequential testing procedure finding structural breaks in the investment-Q relationship. Newey-West standard errors with autocorrelation up to four quarters are reported in parentheses. * and *** denote statistical significance at the 10% and 1% levels, respectively. Constant terms are omitted.

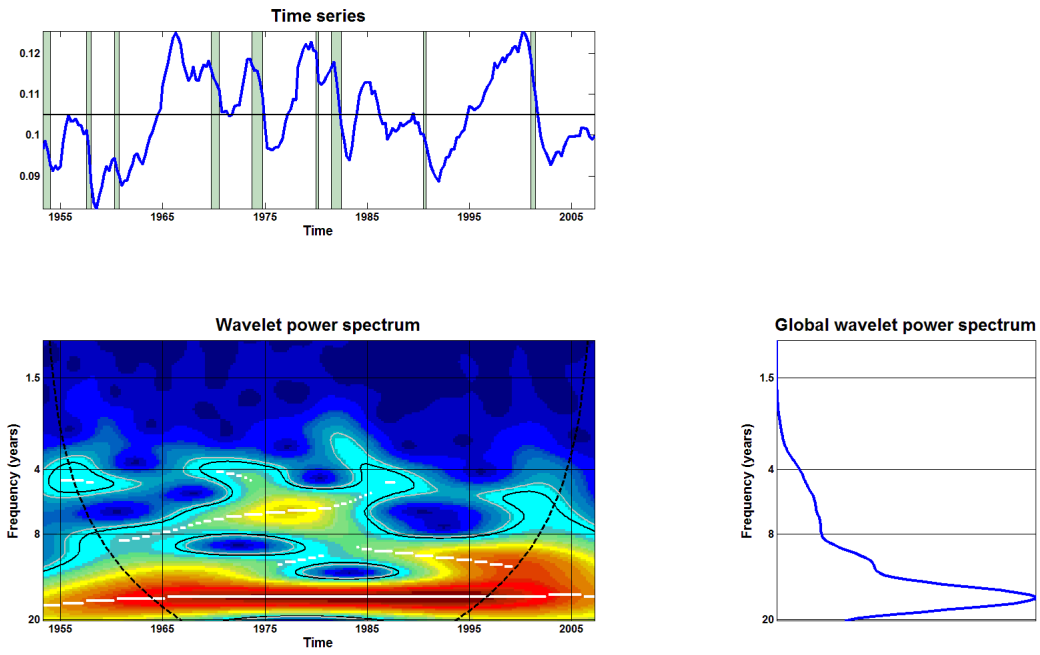

Figure 1: Time series (top graph), wavelet power spectrum (bottom left graph) and global wavelet power spectrum (bottom right graph) of investment rate

Notes. In the time series plots, gray bars denote NBER recessions and the black horizontal line the time series average of the variable. In the power spectrum charts, the color code ranges from blue (low volatility) to red (high volatility). The black (gray) contour marks significance at the 5% (10%) level and the white stripes mark local maxima. Black dashed lines: cone of influence (indicates the region affected by edge effects).

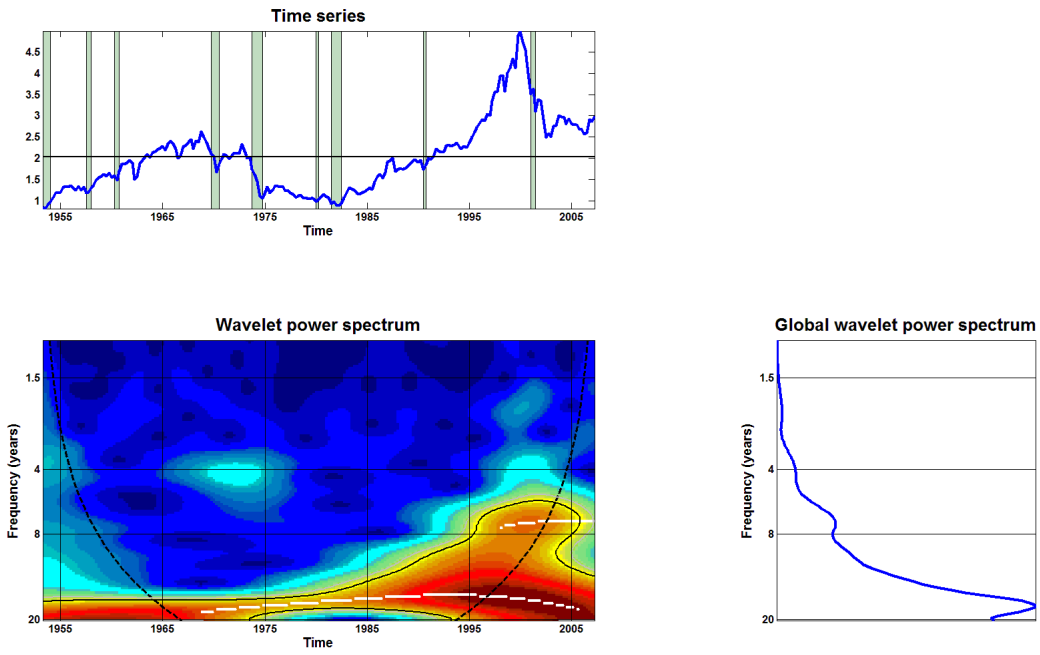

Figure 2: Time series (top graph), wavelet power spectrum (bottom left graph) and global wavelet power spectrum (bottom right graph) of Tobin's Q

Notes. In the time series plots, gray bars denote NBER recessions and the black horizontal line the time series average of the variable. In the power spectrum charts, the color code ranges from blue (low volatility) to red (high volatility). The black (gray) contour marks significance at the 5% (10%) level and the white stripes mark local maxima. Black dashed lines: cone of influence (indicates the region affected by edge effects).

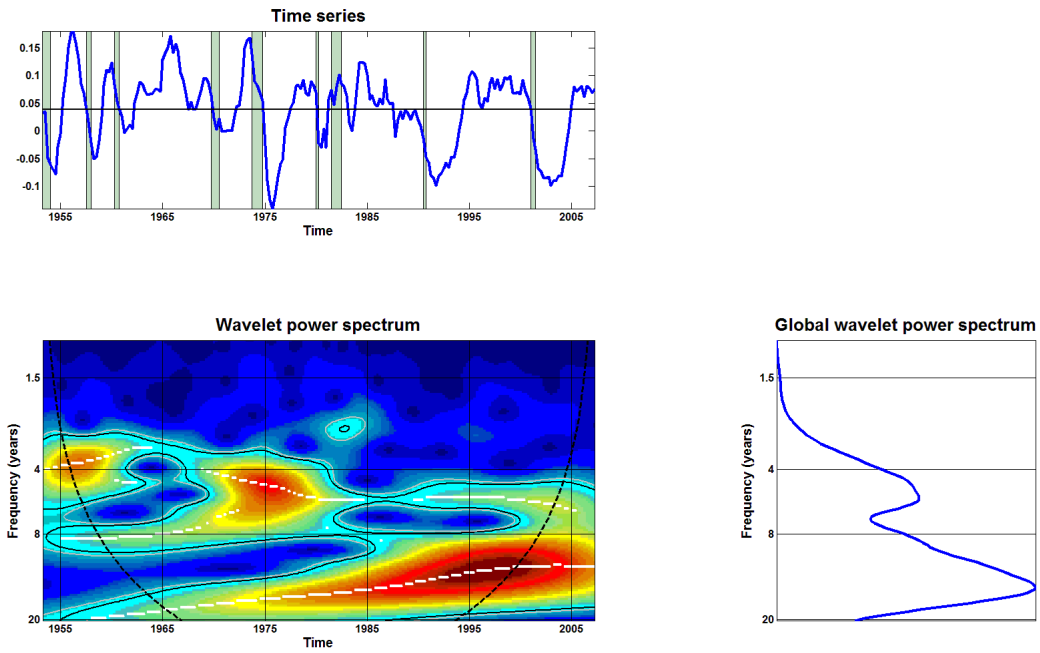

Figure 3: Time series (top graph), wavelet power spectrum (bottom left graph) and global wavelet power spectrum (bottom right graph) of bank loans

Notes. In the time series plots, gray bars denote NBER recessions and the black horizontal line the time series average of the variable. In the power spectrum charts, the color code ranges from blue (low volatility) to red (high volatility). The black (gray) contour marks significance at the 5% (10%) level and the white stripes mark local maxima. Black dashed lines: cone of influence (indicates the region affected by edge effects).

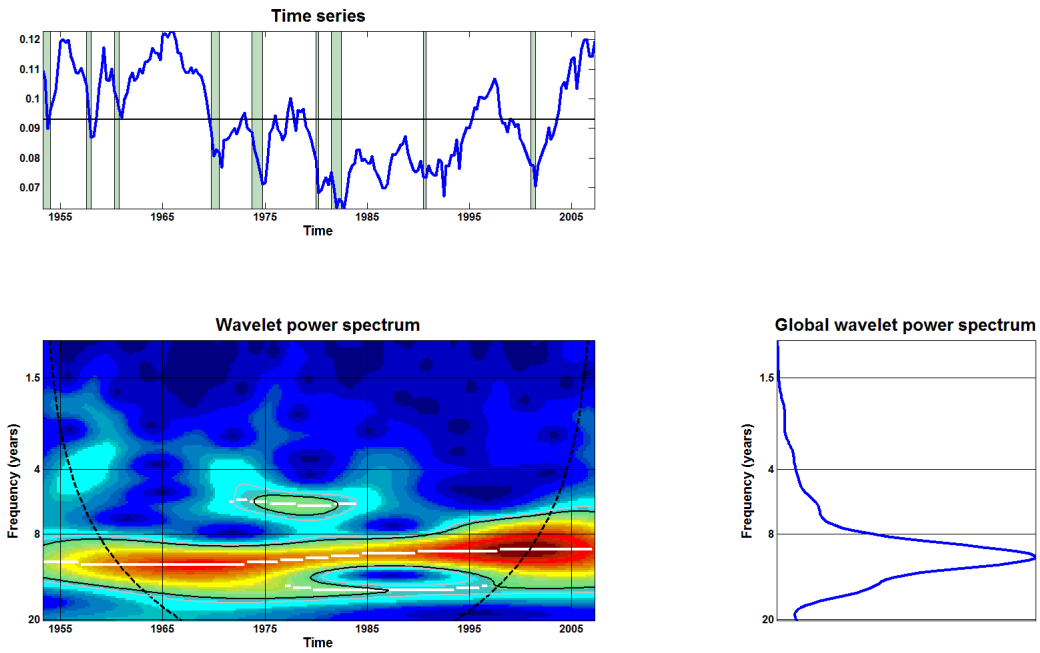

Figure 4: Time series (top graph), wavelet power spectrum (bottom left graph) and global wavelet power spectrum (bottom right graph) of cash flow

Notes. In the time series plots, gray bars denote NBER recessions and the black horizontal line the time series average of the variable. In the power spectrum charts, the color code ranges from blue (low volatility) to red (high volatility). The black (gray) contour marks significance at the 5% (10%) level and the white stripes mark local maxima. Black dashed lines: cone of influence (indicates the region affected by edge effects).

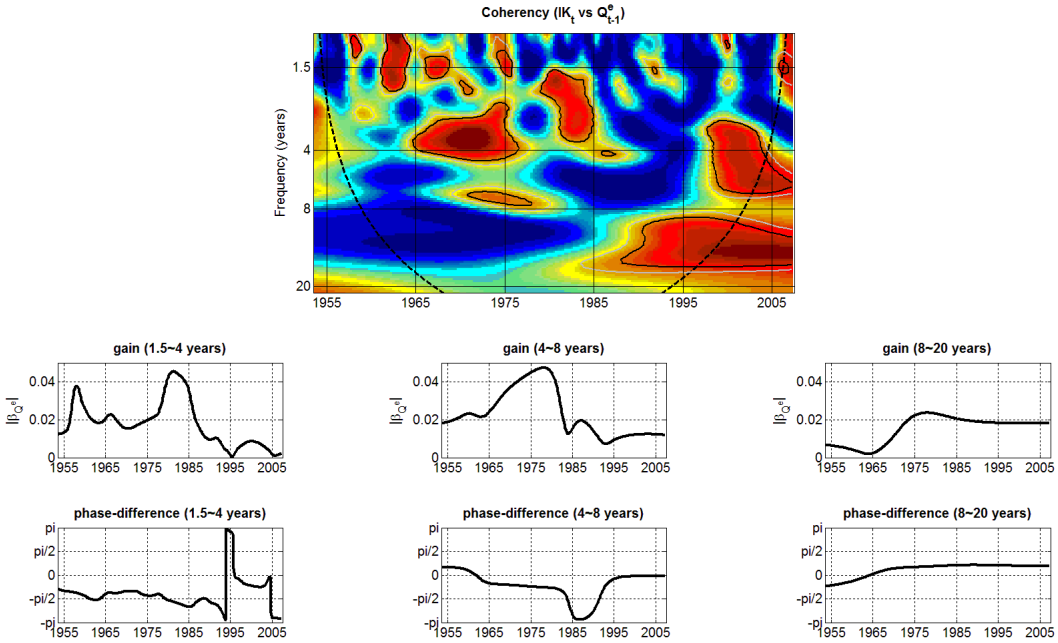

Figure 5: Time-frequency relationship between investment rate and Tobin's Q

Notes. Top graph: wavelet coherence. The color code ranges from blue (low coherence = close to zero) to red (high coherence = close to one). The black (gray) contour designates the 5% (10%) significance level. Black dashed lines: cone of influence (indicates the region affected by edge effects). Middle graphs: wavelet gains for three different frequency intervals. Bottom graphs: wavelet phase-differences for three frequency intervals.

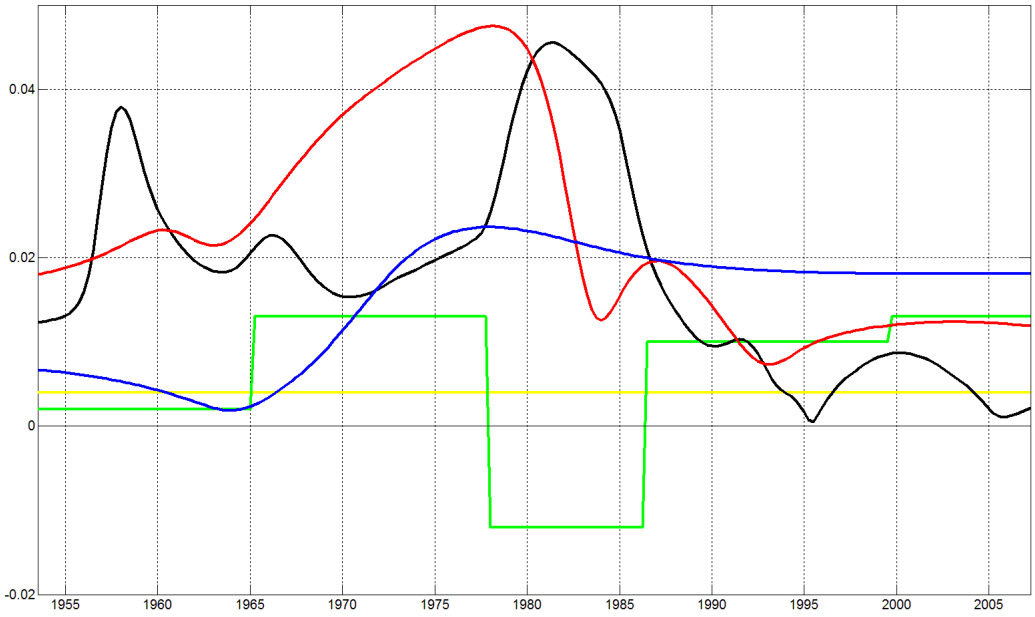

Figure 6: CWT gains ($|\ \beta_{Q^e}\ |$) and OLS regression coefficients (β_{Q^e})

Notes. Yellow line: OLS regression over the entire sample. Green line: OLS sub-sample regression. Black line: wavelet gain ($1.5 \sim 4$-year frequency band). Red line: wavelet gain ($4 \sim 8$-year frequency band). Blue line: wavelet gain ($8 \sim 20$-year frequency band).

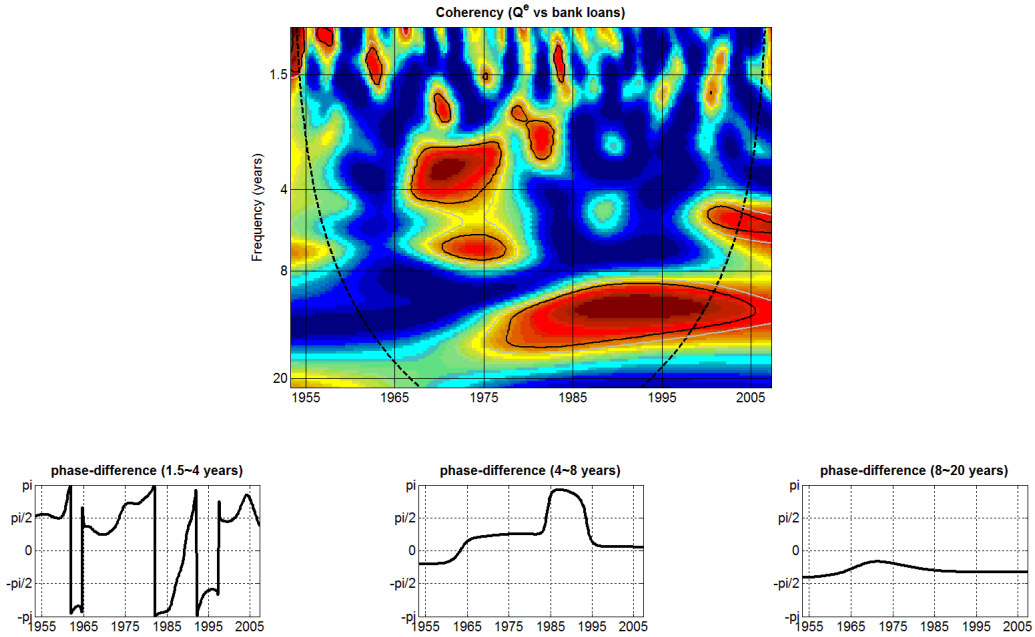

Figure 7: Time-frequency relationship between Tobin's Q and bank loans

Notes. Top graph: wavelet coherence. The color code ranges from blue (low coherence = close to zero) to red (high coherence = close to one). The black (gray) contour designates the 5% (10%) significance level. Black dashed lines: cone of influence (indicates the region affected by edge effects). Bottom graphs: wavelet phase-differences for three frequency intervals.

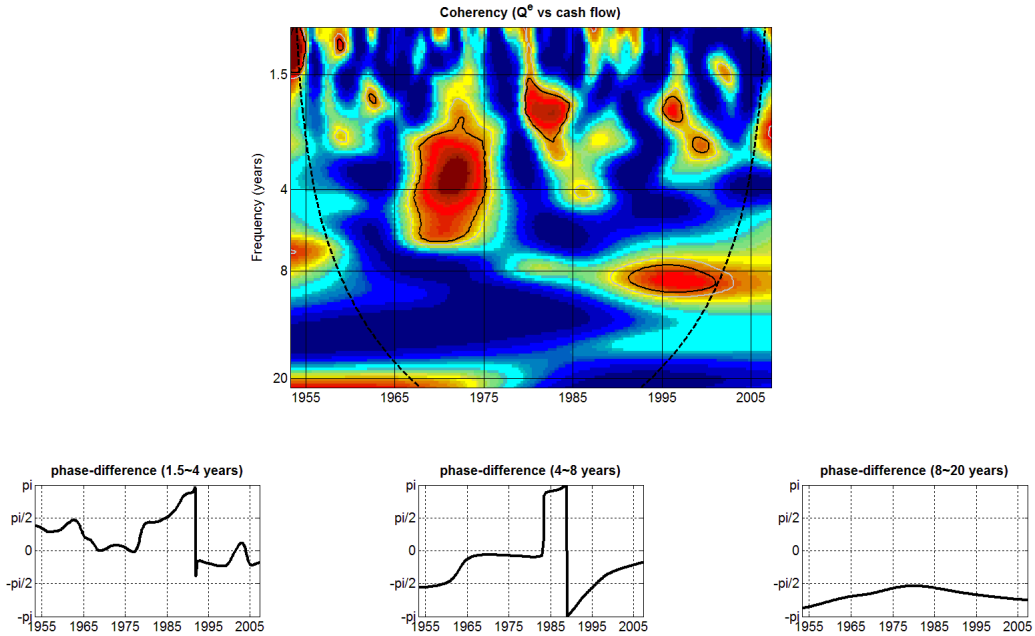

Figure 8: Time-frequency relationship between Tobin's Q and cash flow

Notes. Top graph: wavelet coherence. The color code ranges from blue (low coherence = close to zero) to red (high coherence = close to one). The black (gray) contour designates the 5% (10%) significance level. Black dashed lines: cone of influence (indicates the region affected by edge effects). Bottom graphs: wavelet phase-differences for three frequency intervals.

Online appendix of

"Q, investment, and the financial cycle"

In this online appendix I test the performance of the Q theory

- using the Peters and Taylor (2017) measures of Q and investment that also take into account intangible capital
- applied to housing investment, as first proposed and tested by Takala and Tuomala (1990).

The Q theory with intangible capital and investment

The traditional Q ratio and investment rate only consider the replacement cost of tangible assets, while the US economy has increasingly become service-oriented and driven by intellectual property. Peters and Taylor (2017) propose measures of investment rate and Q that include intangible capital: "total investment" (IK_t^T) and "total Q" (Q_t^T). Total investment is defined as the ratio of the sum of expenditures in physical (I_t^{phy}) and intangible (I_t^{int}) investment relative to the sum of the replacement costs of physical (K_{t-1}^{phy}) and intangible (K_{t-1}^{int}) capital: $IK_t^T \equiv \left(I_t^{phy} + I_t^{int}\right) / \left(K_{t-1}^{phy} + K_{t-1}^{int}\right)$. Total Q is computed as the ratio of the total ownership claims on firm value less the book value of inventories (V_t) relative to the sum of physical and intangible capital: $Q_t^T \equiv V_t / \left(K_{t-1}^{phy} + K_{t-1}^{int}\right)$.

The aggregate data for the US economy is available for the period 1972:Q1-2007:Q2. Figures 1 and 2 show the time series (top graphs), the WPS (bottom left graphs) and the GWPS (bottom right graphs) of total investment and total Q, respectively, and panel A in Table 1 reports the time series correlations between the variables. Total investment displays a cyclical behavior similar to that of the standard measure of

investment (the correlation between them is 0.43). However, due to the increasingly-important contribution of the intangible components over the years, total investment also features a slow upward trend. The WPS shows that two permanent cycles (9 and 18 years) characterize the dynamics of total investment. Total Q exhibits time-series properties quite similar to those of Q^e, as the correlation between them is extremely high (0.997). This is due to the fact that total Q equals Q^e times a ratio that has changed slowly and consistently over time ($Q_t^T = Q_t^e K_{t-1}^{phy} / \left(K_{t-1}^{phy} + K_{t-1}^{int}\right)$).

Visual inspection reveals a strong relationship between total Q and total investment – both trend upward after 1982. This conjecture is confirmed by the relatively high time-series correlation between them (0.77) and by the OLS time series regression of total investment on lagged total Q (Table 2). The Q theory with intangible capital and investment clearly fits the data much better. The fit of the regression is remarkably good (the adjusted R^2 is 61%) and the total-investment-total-Q sensitivity is highly significant and four times larger than with standard measures. Kilponen and Verona (2016) show that the fit of the investment regression with intangible capital and investment is reasonably good in the medium run (R^2 of 23% in the $4 \sim 8$-year frequency band) and extremely good in the long run (R^2s of 69% and 75% in the $8 \sim 16$-year and over-16-years frequency bands, respectively). Hence, the superior performance of the Q theory with intangible capital and investment comes from its good ability to explain the low-frequency trends in Q and investment.

Figure 3 displays the time-frequency relationship between total investment and total Q. As for standard measures, up to 1985 the correlation is high and significant only in the short run. The positive, stable medium-to-long-run relationship begins in the second half of the sample, with total investment leading total Q. Unlike the Q theory with standard measures, this medium-to-long-run relationship starts a few years later (at around 1993 instead of 1985) and at slightly shorter cycles (up to 12 years rather than up to 20 years).

To summarize the results about the magnitude of the total-investment-total-Q sensitivity, Figure 4 reports the wavelet gains (black line: $1.5 \sim 4$-year gain; red line: $4 \sim 8$-year gain; blue line: $8 \sim 20$-year gain) and the result in the time domain (yellow line: OLS regression). Two results deserve mention. First, as with the standard measures, the total-investment-total-Q sensitivities in the time-frequency domain are usually larger than in the time domain. Thus, the CWT allows for further improvement with respect to

standard time series methods even when the results in the time domain are already rather good. Second, the power in the total-investment-total-Q relationship has moved from the short run (1.5 to 4 years) in the first part of the sample to the medium and long run (over 4 years) after 1993, thus indicating that the medium-to-long-run relationship between total investment and total Q began as intangible capital gained importance for the US economy.

Finally, Figure 5 reports the coherence between total Q and bank loans (upper plot) and the phase-difference between them in three frequency ranges (remaining panels). In the $8 \sim 20$-year frequency band, the coherence is high and significant throughout the entire sample, with bank loans leading Q^T. So, as for the standard measures, it seems that credit and booming stock prices reinforced each other, with credit leading and driving a slow, prolonged asset price boom. Furthermore, Figure 6 shows that the long-run relationship between Q^T and the financial cycle also disappears when cash flow is used as a proxy for the financial cycle.

The Q theory of housing investment

While Tobin's original idea has been mainly applied to modeling business investment, Tobin himself suggested that his idea was applicable to housing investment.[1] Researchers have recently shown growing interest in testing how well housing Q, typically defined as the ratio between the value of existing houses and the cost of building new houses, explains residential investment. The idea is that investors and builders find new housing construction attractive when the price of existing houses is higher than the cost of building new ones. Accordingly, residential investment is expected to increase when housing Q is greater than 1.

The first empirical test of the Q theory with housing investment is Takala and Tuomala (1990). The authors find a positive impact of housing Q on residential investments in Finland in the period 1980–1987, but a null impact in the period before (1972–1980). Similar mixed results are found by Berg and Berger (2006) using Swedish data: a stable long-run relationship between several measures of residential investment and the housing Q ratio existed between 1993 and 2003, but not before (between 1981 and 1992). Finally, looking at the US housing market and using three different dependent variables as proxies for residential

[1] See https://www.minneapolisfed.org/publications/the-region/interview-with-james-tobin. Nordby and Taylor (2013) explores the role of Tobin's Q in the office sector.

investment (building starts, building permits, and housing investment expenditures), Jud and Winkler (2003) find a positive and significant effect of housing Q on all dependent variables. Overall, the evidence for housing investment is similar to that for business investment, in that there seems to be a positive unstable relationship between housing Q and residential investment. Analyzing the interaction of the Q theory on the housing market with credit (in form of mortgage loans) is also interesting *per se* given the recent disruptive effects on the global economy caused by credit-fueled housing price bubbles.

To test the Q theory of housing investment, we follow Jud and Winkler (2003) to construct the relevant variables. For the housing investment series (I^H), we take the annual growth rate of the real dollar value of housing investment in single-family structures.[2] Housing Q, denoted Q^H, is defined as the ratio of the value of existing houses to the construction cost of new houses (proxied by the price of new houses). Data for the numerator of Q^H are obtained from the OFHEO price index for existing homes. New home prices (denominator of Q^H) are obtained from the Census Bureau's quality-adjusted series for new home prices. As a proxy for the housing financial cycle, we use the annual growth rate of mortgage loans, which series is available from the flow of funds tables on the Fed Board website. All of the data are quarterly for the period 1975:Q1–2015:Q4 (the mortgage loan series ends at 2013:Q4).

Figures 7, 8 and 9 show the time series (top graphs), the WPSs (bottom left graphs) and the GWPSs (bottom right graphs) of housing investment, housing Q and mortgage loans, respectively. Except for the recession associated with the dot-com bubble in the early 2000s, housing investment exhibits a pro-cyclical behavior, with quick, large drops starting before and persisting until after the end of the respective business cycle recession. Most of the volatility of housing investment occurs at frequencies of about 10 years, given the presence of a permanent cycle at that frequency throughout the sample. A second and longer cycle (about 14 years) is present from 1985 until 2010. The series also exhibits some short-run volatility (red areas at frequencies between 1.5 and 4 years) at the beginning of the sample (until 1987) and during and after the Great Recession. Housing Q exhibits saw-tooth movements, as well as large, low-frequency swings. It moves downward until 1982, trends upward until the end of the Great Recession, and then resumes a downward trend. Throughout the sample, the volatility of Q^H occurs mainly at low frequencies (more than 16 years), with a permanent cycle with a period of about 18 years. The mortgage

[2] Results are similar when using the series of the number of single-family building permits, an alternative variable used by Jud and Winkler (2003).

loans series is characterized by positive (on average 5%) annual growth rates in 80% of the quarters in the sample (90% of the quarters until the end of the Great Recession). The WPS and GWPS shows that the majority of the variability of bank loans occurs at frequencies more than 8 years, and two permanent cycles (9 and 17 years) are visible. Panel B in table 1 reports the correlations between these variables. There is a mild positive correlation (0.39) between housing Q and residential investment, while no correlation (-0.01) between housing Q and mortgage loans.

Figure 10 displays the time-frequency relationship between residential investment and housing Q. The overall fit of the housing investment equation in the time-frequency domain is not quite as good as that with business investment. There is some positive correlation at high frequencies (1.5 to 4 years) until 2000, while the stable medium-to-long-run correlation starts from the early 2000s and is mainly concentrated at frequencies between 6 and 12 years. From the phase-difference, the correlation in that time-frequency region is actually negative, with housing Q leading residential investment.

Figure 11 reports the coherence between Q^H and mortgage loans (upper plot) and the phase-difference between them in three frequency intervals (remaining panels). At frequencies below 8 years, there is evidence of an unstable correlation between Q^H and credit. However, in the $8 \sim 20$-year frequency band and from 1985 onward, the correlation is high and positive, with mortgage loans leading Q^H. As in the business investment case, it appears that credit (in form of mortgage loans) and booming house prices reinforce each other, with credit leading and fueling the slow and prolonged house price boom that starts in 1982.

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Panel A: Intangible variables				
	IK^T	Q^T	bank loans	cash flow
IK^T	1			
Q^T	0.77	1		
bank loans	0.30	0.06	1	
cash flow	0.40	0.41	0.20	1

Panel B: Housing market variables			
	I^H	Q^H	mortgage loans
I^H	1		
Q^H	0.39	1	
mortgage loans	0.62	-0.01	1

Table 1: Correlation matrix

Notes. This table reports the time-series correlation between the variables. Data for cash flow and bank loans are from Philippon (2009) and Contessi et al. (2015), respectively, while for IK^T and Q^T are from Peters and Taylor (2017); quarterly data, 1972:Q1 to 2007:Q2. Data for I^H and Q^H are computed as in Jud and Winkler (2003), and data for mortgage loans from Contessi et al. (2015); quarterly data, 1975:Q1 to 2013:Q4.

		Dependent variable IK_t^T
Q_{t-1}^T	β_{Q^T}	0.017***
	s.e.	(0.003)
	obs	141
	$\bar{R}^2$	0.614

Table 2: Investment regressions

Notes. Data for IK^T and Q^T are from Peters and Taylor (2017); quarterly data, 1972:Q1 to 2007:Q2. Newey-West standard errors with autocorrelation up to four quarters are reported in parentheses. * and *** denote statistical significance at the 10% and 1% levels, respectively. Constant terms are omitted.

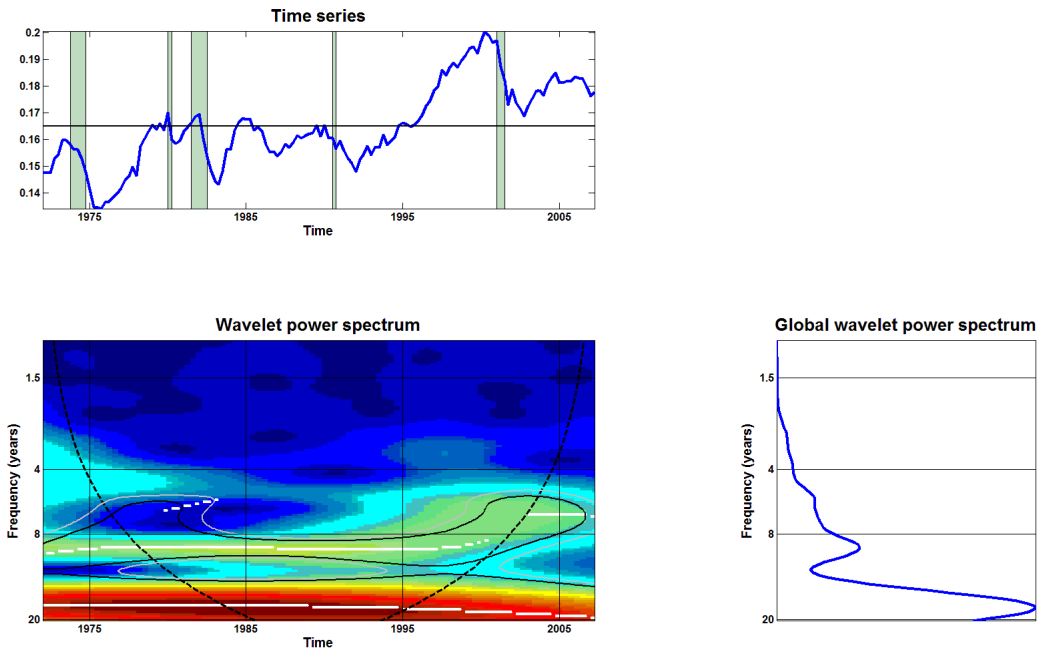

Figure 1: Time series (top graph), wavelet power spectrum (bottom left graph) and global wavelet power spectrum (bottom right graph) of total investment rate

Notes. In the time series plots, gray bars denote NBER recessions and the black horizontal line the time series average of the variable. In the power spectrum charts, the color code ranges from blue (low volatility) to red (high volatility). The black (gray) contour marks significance at the 5% (10%) level and the white stripes mark local maxima. Black dashed lines: cone of influence (indicates the region affected by edge effects).

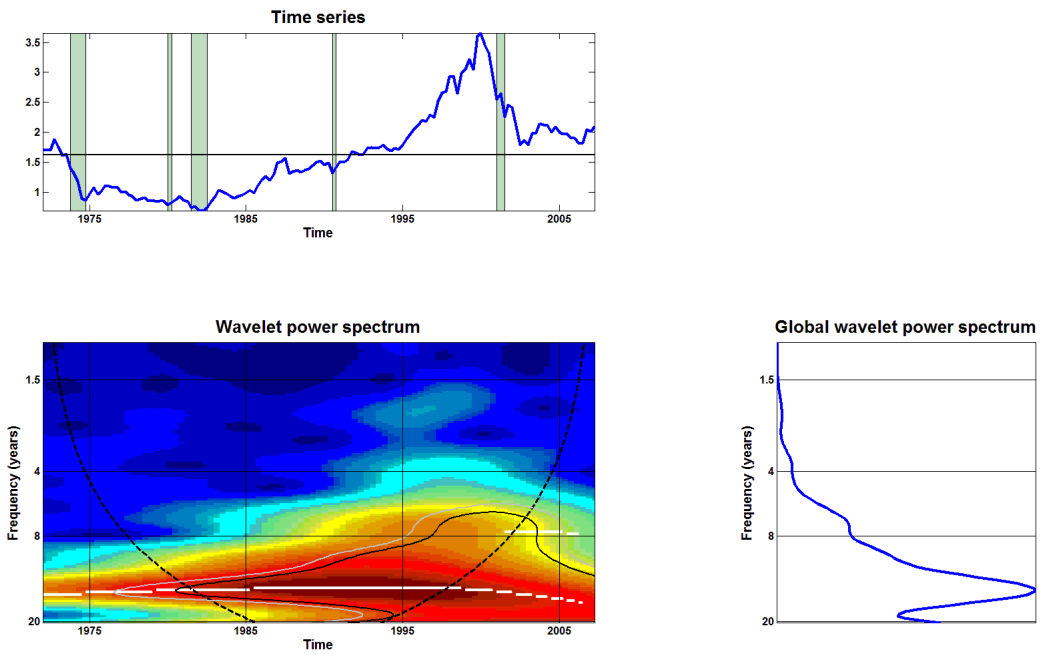

Figure 2: Time series (top graph), wavelet power spectrum (bottom left graph) and global wavelet power spectrum (bottom right graph) of total Tobin's Q

Notes. In the time series plots, gray bars denote NBER recessions and the black horizontal line the time series average of the variable. In the power spectrum charts, the color code ranges from blue (low volatility) to red (high volatility). The black (gray) contour marks significance at the 5% (10%) level and the white stripes mark local maxima. Black dashed lines: cone of influence (indicates the region affected by edge effects).

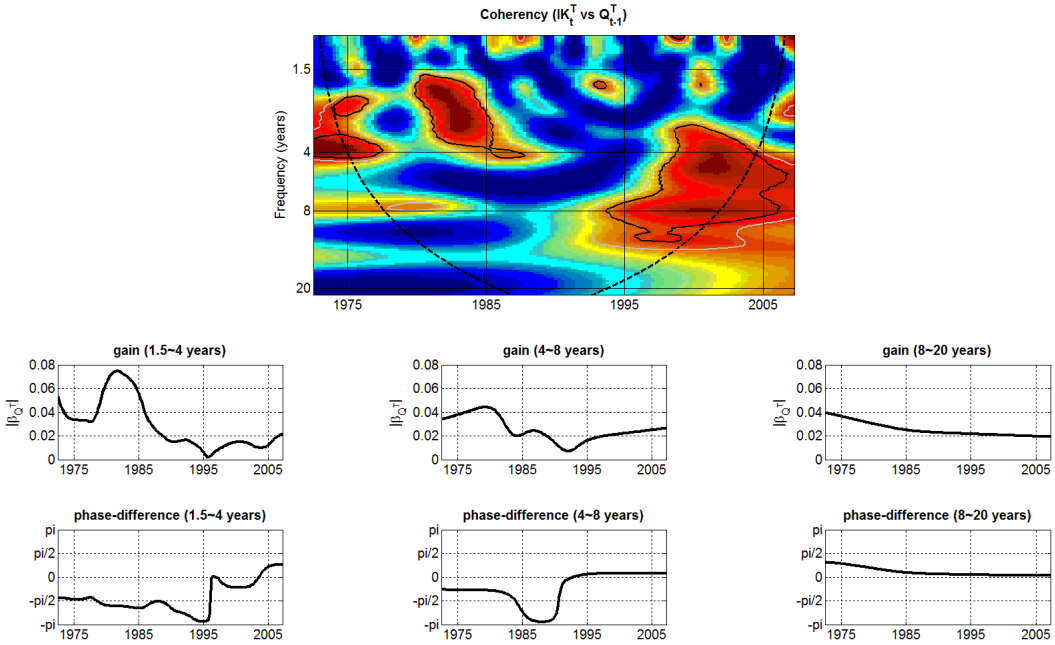

Figure 3: Time-frequency relationship between total investment and total Tobin's Q

Notes. Top graph: wavelet coherence. The color code ranges from blue (low coherence = close to zero) to red (high coherence = close to one). The black (gray) contour designates the 5% (10%) significance level. Black dashed lines: cone of influence (indicates the region affected by edge effects). Middle graphs: wavelet gains for three frequency intervals. Bottom graphs: wavelet phase-differences for three frequency intervals.

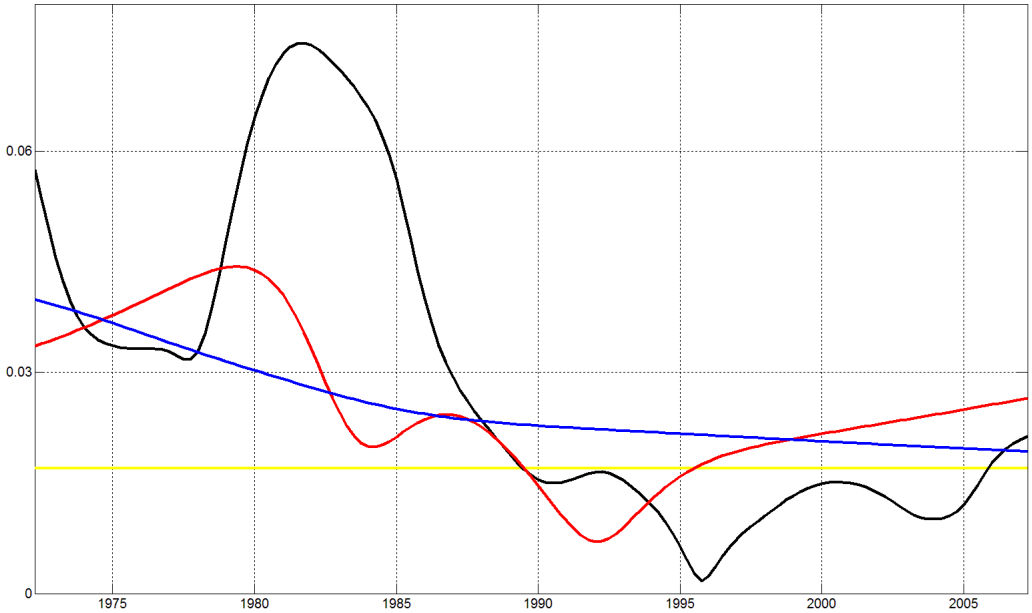

Figure 4: CWT gains ($|\ \beta_{Q^T}\ |$) and OLS regression coefficient (β_{Q^T})

Notes. Yellow line: OLS regression over the entire sample. Black line: wavelet gain (1.5 $\sim$ 4-year frequency band). Red line: wavelet gain (4 $\sim$ 8-year frequency band). Blue line: wavelet gain (8 $\sim$ 20-year frequency band).

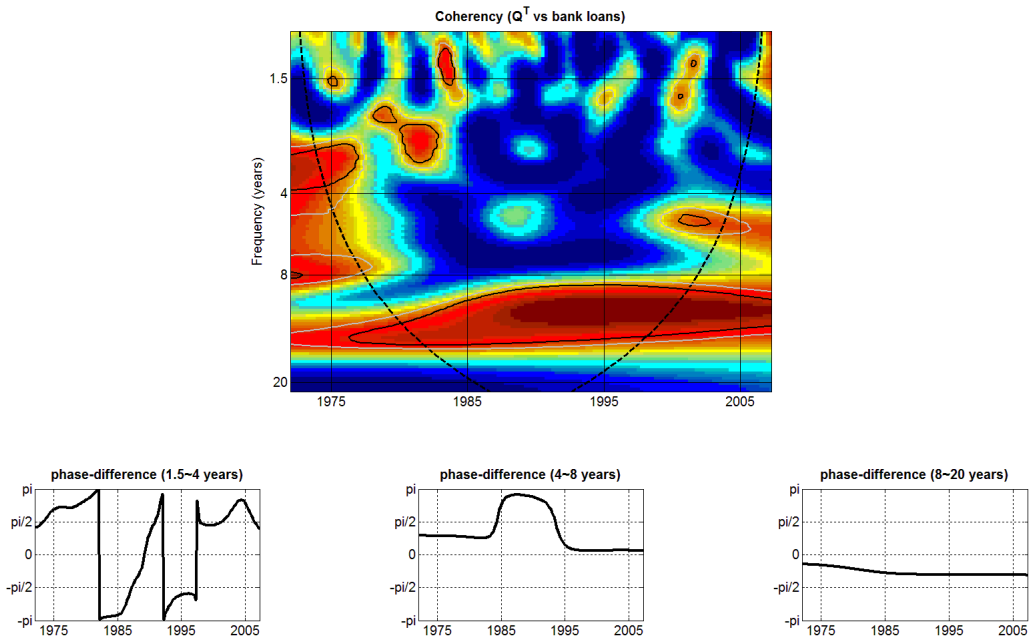

Figure 5: Time-frequency relationship between total Q and bank loans

Notes. Top graph: wavelet coherence. The color code ranges from blue (low coherence = close to zero) to red (high coherence = close to one). The black (gray) contour designates the 5% (10%) significance level. Black dashed lines: cone of influence (indicates the region affected by edge effects). Bottom graphs: wavelet phase-differences for three frequency intervals.

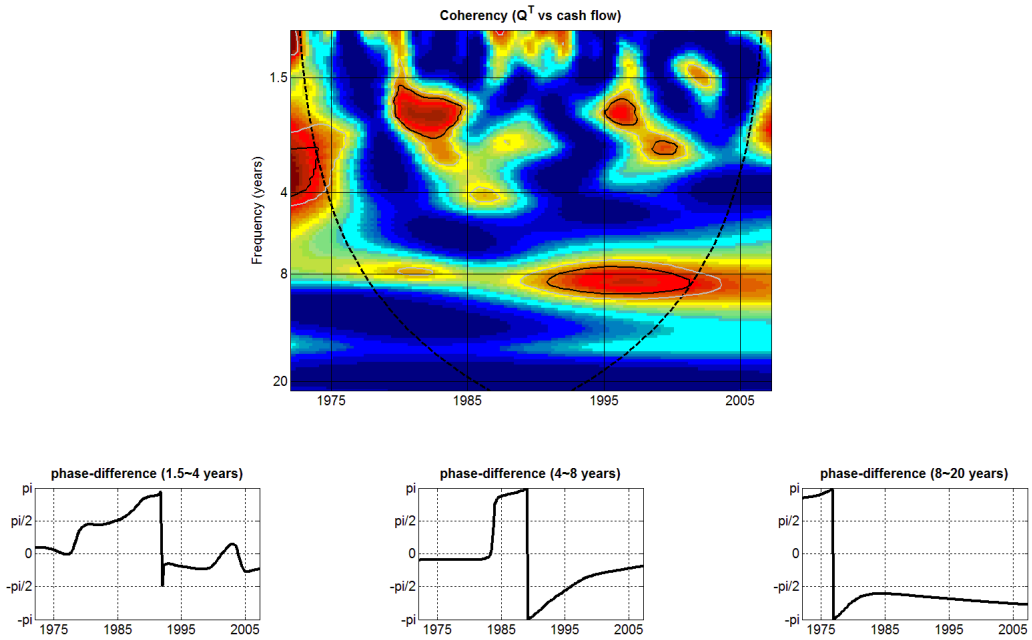

Figure 6: Time-frequency relationship between total Q and cash flow

Notes. Top graph: wavelet coherence. The color code ranges from blue (low coherence = close to zero) to red (high coherence = close to one). The black (gray) contour designates the 5% (10%) significance level. Black dashed lines: cone of influence (indicates the region affected by edge effects). Bottom graphs: wavelet phase-differences for three frequency intervals.

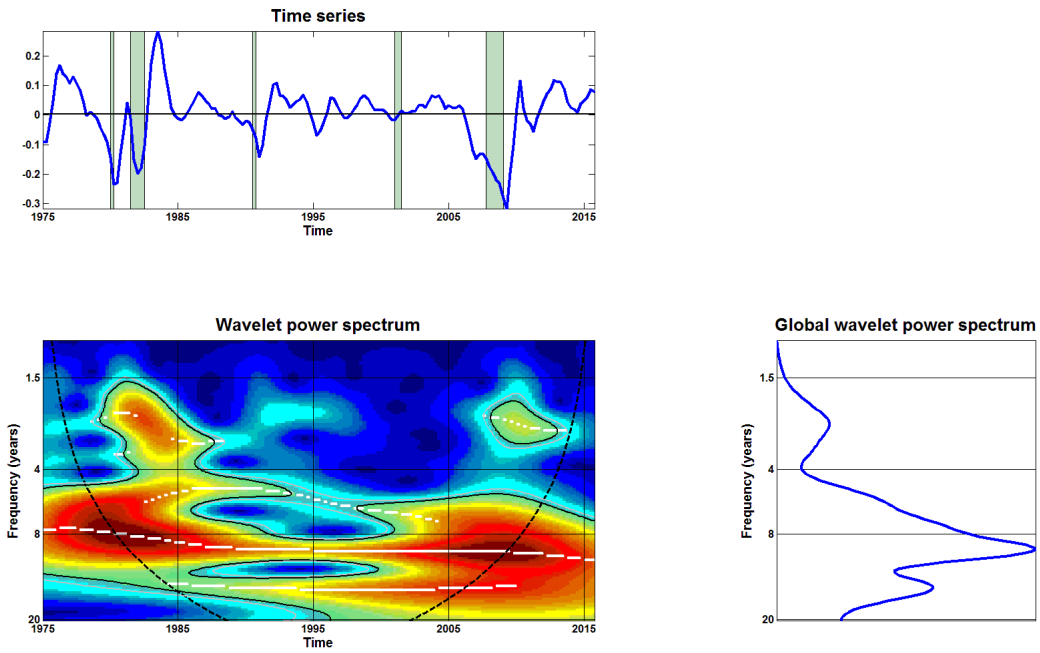

Figure 7: Time series (top graph), wavelet power spectrum (bottom left graph) and global wavelet power spectrum (bottom right graph) of housing investment

Notes. In the time series plots, gray bars denote NBER recessions and the black horizontal line the time series average of the variable. In the power spectrum charts, the color code ranges from blue (low volatility) to red (high volatility). The black (gray) contour marks significance at the 5% (10%) level and the white stripes mark local maxima. Black dashed lines: cone of influence (indicates the region affected by edge effects).

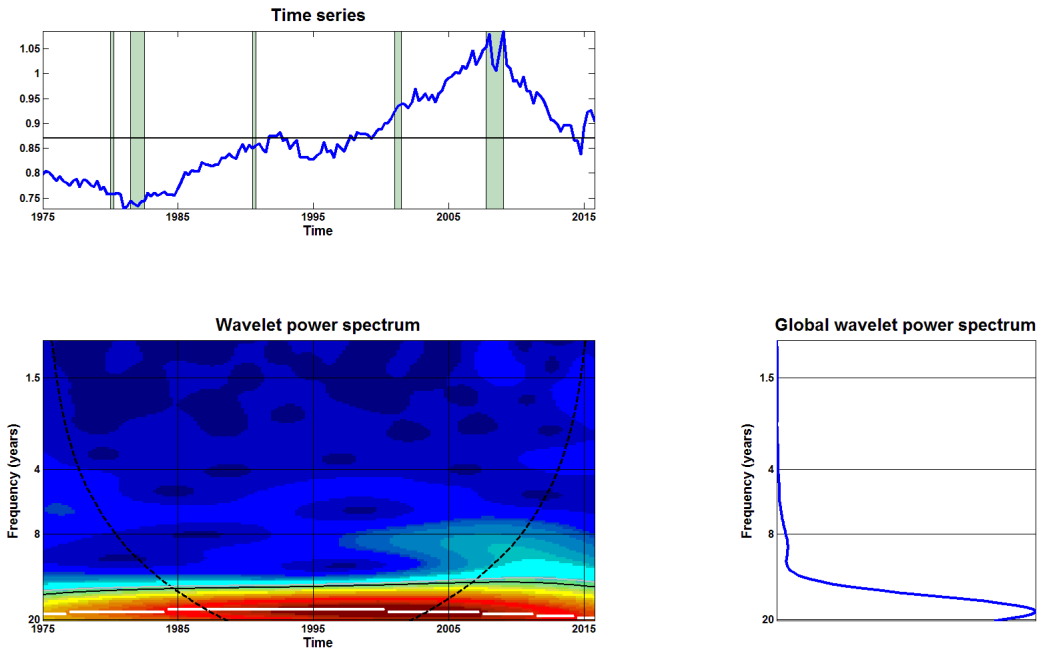

Figure 8: Time series (top graph), wavelet power spectrum (bottom left graph) and global wavelet power spectrum (bottom right graph) of housing Q

Notes. In the time series plots, gray bars denote NBER recessions and the black horizontal line the time series average of the variable. In the power spectrum charts, the color code ranges from blue (low volatility) to red (high volatility). The black (gray) contour marks significance at the 5% (10%) level and the white stripes mark local maxima. Black dashed lines: cone of influence (indicates the region affected by edge effects).

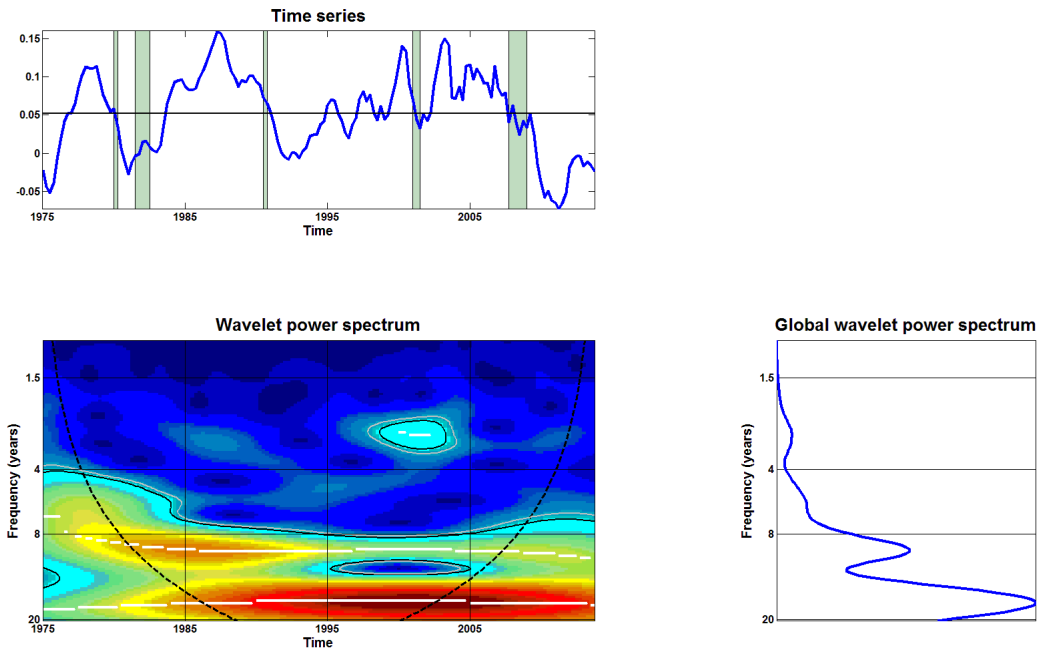

Figure 9: Time series (top graph), wavelet power spectrum (bottom left graph) and global wavelet power spectrum (bottom right graph) of mortgage loans

Notes. In the time series plots, gray bars denote NBER recessions and the black horizontal line the time series average of the variable. In the power spectrum charts, the color code ranges from blue (low volatility) to red (high volatility). The black (gray) contour marks significance at the 5% (10%) level and the white stripes mark local maxima. Black dashed lines: cone of influence (indicates the region affected by edge effects).

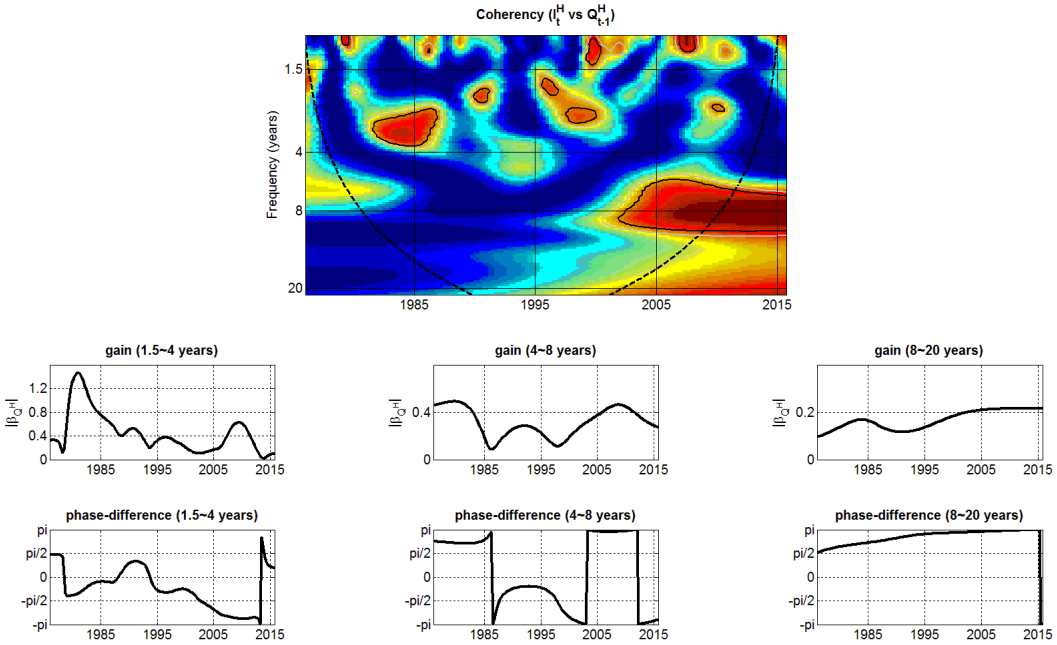

Figure 10: Time-frequency relationship between housing investment and housing Q

Notes. Top graph: wavelet coherence. The color code ranges from blue (low coherence = close to zero) to red (high coherence = close to one). The black (gray) contour designates the 5% (10%) significance level. Black dashed lines: cone of influence (indicates the region affected by edge effects). Middle graphs: wavelet gains for three frequency intervals. Bottom graphs: wavelet phase-differences for three frequency intervals.

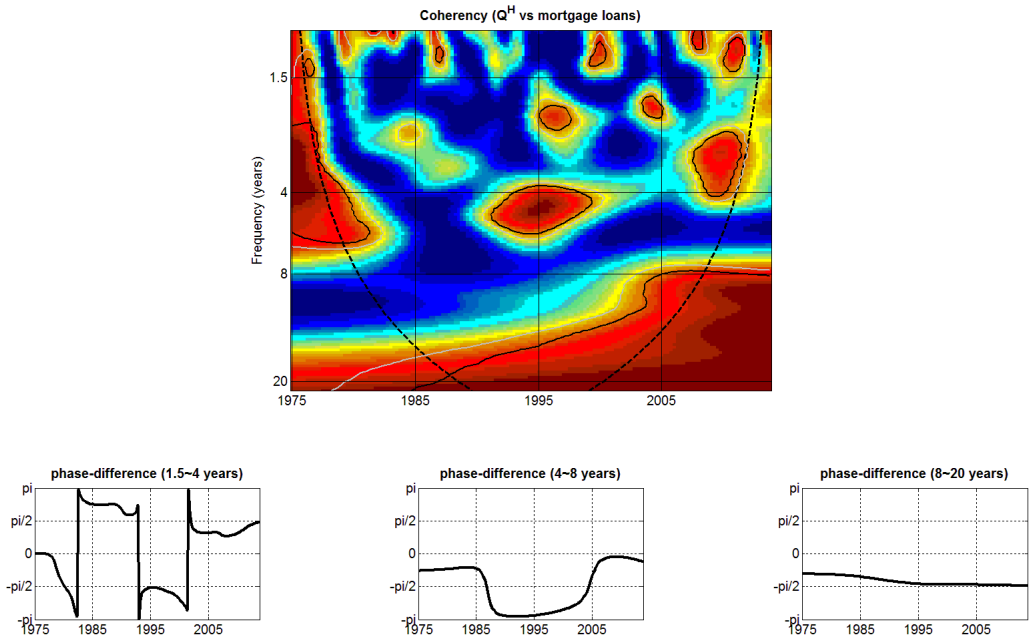

Figure 11: Time-frequency relationship between housing Q and mortgage loans

Notes. Top graph: wavelet coherence. The color code ranges from blue (low coherence = close to zero) to red (high coherence = close to one). The black (gray) contour designates the 5% (10%) significance level. Black dashed lines: cone of influence (indicates the region affected by edge effects). Bottom graphs: wavelet phase-differences for three frequency intervals.

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