VC FINANCING AND MARKET GROWTH – INTERDEPENDENCIES BETWEEN TECHNOLOGY-PUSH AND MARKET-PULL INVESTMENTS IN THE US SOLAR INDUSTRY

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Abstract

Drawing from literatures on VC decision making and innovation studies, scholars have identified linkages between technological innovation and market growth: VC research has studied the role of firms’ technological capabilities and market opportunities for VC decision making. Innovation research examined the influence of technology-push and market-pull as sources of innovation. Previous research has investigated these effects independently. Our study is the first to perform a joint examination of interdependent effects between technology and market. We examine interdependencies between investment in technology and in capacity by analyzing the endogenous relationship between VC investment in solar technology firms and asset finance investment in solar power infrastructure capacity in the US. Using a vector-autoregressive model for investment data from Bloomberg New Energy Finance (BNEF) we find that investment in solar technology strongly drives investment in solar capacity; however, market growth caused by solar capacity investment induces only weakly follow-on investment by solar technology VCs. This paper contributes to the literature on VC decision-making and the technology-push versus market pull debate.

Keywords: Venture Capital; VC decision making; VC involvement; Asset Finance; Infrastructure Finance; Technology-push; Market-pull; Solar Technology; Vector autoregression (VAR)

JEL codes: D81 - Criteria for Decision-Making under Risk and Uncertainty; G24 - Investment Banking; Venture Capital; Brokerage; Ratings and Ratings Agencies; L26 – Entrepreneurship; Q01 - Sustainable Development; Q55 - Technological Innovation
VC financing and market growth - Interdependencies between technology-push and market-pull investments in the US solar industry

1 Introduction

For venture capital (VC) investors in early- and growth-stage technology companies, the technological capability of the investment target and founder experience plays an important role in decision-making (Shepherd, 1999; Colombo and Grilli, 2010; Eckhardt & Shane, 2011; Kotha & George, 2012; Aggarwal, Kryscinski and Singh, 2015). Moreover, market opportunities of a technology, in terms of size and growth characteristics, play an important role for investment decisions (Gruber, MacMillan and Thompson, 2008; Petty and Gruber, 2011; Gerasymenko & Arthurs, 2014). On the other hand, VC investments contribute to subsequent portfolio firm growth, but not profitability (Bertoni, Colombo & Grilli, 2011; Croce, Martì & Murtinu, 2013; Rosenbusch, Brinckmann & Müller, 2013; Bhaumik, Fraser and Wright, 2015).

However, the ability of early- or growth-stage investors to influence market opportunities of asset-heavy technologies through their investments is rather limited (Criscuolo & Menon, 2015). Instead, growth dynamics of these markets are influenced by other sources of capital, in particular, institutional investors such as pension funds, endowments, insurance companies, banks, and other corporations. In consequence, technology investments can stimulate the development of new or more efficient products thereby generating technology-push effects, whereas infrastructure or capacity investments can stimulate higher demand for these technologies and products thereby generating market-pull effects. While both of these reactions are widely accepted (Mowery and Rosenberg, 1979; Rennings, 2000; Costantini, Crespi, Martini and Penacchio, 2015), relatively little attention has been dedicated to the interdependencies between technology-push and market-pull mechanisms (e.g. Arthur, 2007; Di
Stefano, Gambardella and Verona, 2012). Notably, most of this research is policy- and product-oriented and pays little attention to (entrepreneurial) finance perspectives such as venture capital.

Following this rationale, we aim to answer the following research question: how does VC investment influence AF investment (and vice versa)? More specifically, do VC investments in solar technologies/products drive the solar infrastructure market or does asset finance drive VC? In the latter case, do VC investors wait for proof of concept and hence investment by AF investors to drive the solar infrastructure market before committing capital?

The solar technology sector provides an interesting opportunity to investigate these aspects (Petkova, Wadhwa, Yao and Jain, 2014; Kapoor & Furr, 2014): as an industry, the solar technology sector is comparatively young, and significant policy effort has been made in the past decade to improve its technological efficiency and competitiveness. In addition, policies have been dedicated to increasing the market size and capacity of solar technology field installations. Solar is one of the industries where large part of demand stems from business-to-business customers such as solar park developers, utilities or other big corporations in need of (renewable) energy. Therefore, investments in solar technology companies should stimulate the development of new or more efficient products (e.g. photovoltaic modules) and hence create technology push, whereas infrastructure and capacity investments (e.g. investments in power plants / energy generation) should generate market-pull. Similarly, capacity investment in solar power infrastructure should increase market opportunities for solar technology firms’ products and technologies. In order to investigate the interdependencies described in our research question we analyze a dataset for investments in the US solar industry 2001-2012 from Bloomberg New Energy Finance (BNEF), a leading data provider for renewable energies (Criscuolo and Menon, 2015; Polzin, Migendt, Täube and v. Flotow, 2015).

\[5\] For instance, Apple, Google, Facebook and Microsoft have been building huge solar (and wind) parks to power their server farms (Goldenberg, 2014)
We use impulse-response functions, Granger causality tests and forecast error variance decomposition based on a vector autoregression (VAR) model (Coad, 2010). An impulse-response function shows the reaction of a change in one variable (response) as a function of a change in another variable (impulse). The variance decomposition shows what percentage of the change in one variable can be explained by the change in another variable.

By analyzing the interrelations between VC investment and AF investment in the solar sector, we contribute to a number of strands in the literature. First, we contribute to the literature on VC decision-making (MacMillan, Siegel, & Narasimha, 1985; Shepherd, 1999; Petty & Gruber, 2011; Aggarwal et al., 2015). Within the scope of our VAR model, we are able to empirically test to what extent market dynamics such as demand growth and market volume affect VC investments.

Second, the model enables us to assess the impact of technology investment on capacity investment that reflects the dynamics of the market. As a consequence, we contribute to the literature investigating the impact of VC investments on innovation and technology development. We thereby extend prior work regarding the VC-innovation relationship addressing the question of whether innovative behavior is induced by VC firms (VC-First thesis) or whether firms that received VC funds were already more innovative than their peers prior to the investment (Innovation-First thesis) (Bertoni et al., 2011; Croce et al., 2013; Rosenbusch et al., 2013).

Finally, by examining the interdependent relationships between VC investment in solar technology firms and AF investment in solar power infrastructure capacity, we contribute to the ongoing debate on technology-push and market-pull (Audretsch, Heger, & Veith, 2014; Woolley, 2014). Specifically, we can determine whether the impact of technology investment that drives market dynamics is larger or smaller than the impact of market dynamics on technology investment.
The remainder of this paper proceeds as follows: Chapter 2 lays the theoretical background. Chapter 3 describes our research context followed in chapter 4 by a description of the data and model used to analyze the interrelation between technology investments and capacity investments in the solar sector. Chapter 5 continues with the results from the VAR analysis and some supplementary analyses and robustness checks. Chapter 6 discusses our findings against prior literature and concludes with theoretical and practical implications.

2 Theoretical background

Studies on VC decision making have shown that the criteria that VC investors use to select from among potential portfolio companies can be divided into four major categories: (1) market-related criteria, (2) product/technology-related criteria, (3) management-related criteria, and (4) financial criteria (Tyebjee & Bruno 1984; Shepherd, 1999; Gompers & Lerner, 2001; Kaplan et al., 2009; Colombo & Grilli, 2010; Eckhardt & Shane, 2011; Kotha & George, 2012; Aggarwal, Kryscinski & Singh, 2015). Although additional VC-firm-specific selection criteria exist and the categorization of the criteria slightly varies among different studies, the four broad categories mentioned above are typically present in almost all the studies on VC decision-making. In their work on VC, Gompers and Lerner (2001) describe how successful VC managers emphasize different criteria in their decision-making process: Whereas some VCs focus on the product/technology (Kaplan et al., 2009), other VCs focus on market dynamics Gruber, MacMillan & Thompson, 2008; Petty & Gruber, 2011; Gerasymenko & Arthurs, 2014), and still other VCs consider the management team the most decisive factor (Colombo & Grilli, 2010). Within these broad decision-making categories, prior research has indicated that market and technology/product-related decision

6 Additional criteria can include industry or regional focus, funding status and/or existing composition of company portfolio among others.
criteria are used more frequently to approximate future returns (Kaplan et al., 2009), whereas management-related decision criteria often consider risk mitigation (Lerner, 2012; Tyebjee & Bruno, 1984).

Other studies have shown differential effects on portfolio firm performance (Rosenbusch et al., 2013). On one hand, some literature found VC investment to be associated with a significant effect on innovative output, as measured by the quantity and quality of patents issued following a VC investment and the commercialization of innovations in general (Tyková, 2000; Kortum & Lerner, 2002). On the other hand, according to recent meta-analysis and literature studies it seems now well-accepted that VC firms positively affect growth, but not profitability of portfolio firms, while the mechanism of VC impact is still debated, (Rosenbusch et al., 2013; Bhaumik et al, 2015). At the core of this debate is the question, to which extent VC firms screen and select or rather treat their portfolio firms to add value (Bertoni, Colombo & Grilli, 2011; Croce, Martí & Murtinu, 2013).

Effects beyond the individual VC firms are seen in an impact on the end-user market for these specific technologies (Croce et al., 2013) and in a growing market volume as well as feedback-loops to attracting further VC investments (Kaplan, Sensoy, & Strömberg, 2009; Petty & Gruber, 2011; Tyebjee & Bruno, 1984).

Correspondingly, there seems to be unanimous understanding that there are positive effects of VC investment on portfolio firms, such as growth, even if the mechanism is still somewhat unclear. On the other hand, there is an effect of growth potential (among others) on VC investment. However, both of these effects have been treated individually and unidirectional. To the best of our knowledge, there is no simultaneous analysis of the endogenous relationship between VC investment and growth.
Similarly, extant research has shown that both technology-push and market-pull are important factors for innovation in general (Di Stefano et al., 2012) and solar technology innovation in particular (Peters et al., 2012), yet there are limited studies of interaction effects (Arthur, 2007; Nemet, 2009; Hoppmann et al., 2014). This is puzzling as the dynamic interrelations between these two are important in explaining the overall progress of innovation (Kline and Rosenberg, 1986). Moreover, extant research focuses on innovation policy geared towards technology-push or market-pull (Taylor, 2008; Nemet, 2009; Peters, Schneider, Griesshaber and Hoffmann, 2012; Hoppmann, Peters, Schneider and Hoffmann, 2013; Costantini et al., 2015). However, even recent efforts addressing interdependencies still focus on policy-induced effects (Nemet, 2009; Di Stefano et al., 2012; Peters et al., 2012; Hoppmann et al., 2013) and very little attention has been devoted to technological research versus market-creation as a consequence of private sector financing.

Finally, scholars have considered a linear process of market commercialization and diffusion of innovations by a single firm. This does not apply to industries where technology invented – and commercialized – by one (entrepreneurial) firm is typically deployed by (an)other large firm(s) on a larger scale (Hockerts & Wüstenhagen, 2010). Therefore, the question of technology-push versus market-pull is less integrated with regard to investment decision-making than in industries with one firm acting along the entire value chain.\(^7\)

To summarize, there is a gap in both entrepreneurial finance and innovation research on the interdependent effects of VC involvement on firm performance and growth potential on VC investment. Therefore, our research question is directed at investigating these interdependencies.

\(^7\) We do not intend to say that there are no firms present along the entire value chain; however, this is more of an exception with a clear separation between innovation and diffusion being executed by different entities.
3 Research context

We chose the solar industry in the US 2001-2012 as our empirical setting to investigate our arguments about interdependencies between VC and capacity investments. As a sizable part of renewable energies, the solar industry is object of several policy initiatives – primarily focusing on market-pull effects and technology exploitation through feed-in tariffs and loan guarantees to technology ventures (Ardani and Margolis, 2011; Hargadon & Kenney, 2012).

Despite the uncertainties of this new industry, VCs invest in solar ventures and face challenges of a fragmented value chain and high capital intensity (Kapoor & Furr, 2014). Therefore, some policy initiatives have played a role in assuring investors. In particular, the loan guarantees often went to firms already backed by VCs and thereby illustrate the interdependencies (Hargadon & Kenney, 2011).

Overall, the solar industry has witnessed a lot of investments in both technology and capacity (Schock, v. Flotow & Täube, 2014), which can be measured by VC (Criscuolo & Menon, 2015) and asset finance transactions (Polzin et al., 2015). The possibility to observe these investments make the solar industry an ideal setting to investigate our research question.

3.1 Industry background

The solar industry is characterized by several idiosyncrasies, notably in industry structure, such as “discontinuous” value chains. VC investment in companies operating in the solar technology sector (i.e. technology developers and equipment manufacturers) can be categorized as investment that ultimately funds new technologies and/or drives the commercialization of new technologies. On the other hand, the effort to increase size and capacity of solar power generation can be approximated by measuring asset finance (AF) investment in solar infrastructure projects. In the case of the latter, it is clear that an increase in AF investment leads directly to an increase in capacity and hence an increase in overall size for solar technology market opportunities.
The availability of improved technologies is likely to stimulate further growth of solar power infrastructure investments through providers of asset finance such as utility companies, corporates, municipalities and banks among others, which benefit from the increased solar technology cost efficiency. In turn, market growth rates and overall market size stimulated by asset finance investors constitute important factors for VC investors to consider when allocating capital to firms in different sectors and industries, according to research on VC decision-making. In the solar technology sector the technology application is driven by capacity investment in solar power infrastructure. Therefore, as capacity investment in solar power infrastructure increase over time, so does the market for solar technology companies. This consequently increases the attractiveness of the solar technology sector for technology investors, that is, VC that value market characteristics in their decision-making process. Specifically, as long as the market continues to grow, new entrants face comparatively less severe competition compared to saturated markets and market shares and hence attractive returns on investment can be gained more easily. Following this rationale, decision-making theory suggests that increases in capacity investment in solar power infrastructure lead to increases in VC investment in solar technology companies in the subsequent periods. Figure 1 provides a stylized overview of the solar technology value chain and depicts the main research question of this paper (for a more detailed view of the solar technology value chain see Appendix, Figure 5-3): (how) does VC investment influence AF investment (and vice versa)?

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8 In the period from 2001 to 2012, almost 90% of asset finance investments as measured by BNEF were conducted by utility companies, large corporations such as Google and Costco, oil & gas companies, governmental institutions or municipalities as well as financial infrastructure investors, all of which typically don’t invest in solar technology manufacturing companies and rely on external suppliers of solar technology equipment.

9 From a commercial perspective, market growth is an indicator of revenue growth whereas the size of a market is an indicator of the overall revenue potential albeit competitive behavior of other market participants obviously also plays an important role.
4 Empirical methodology

4.1 Econometric Model

In order to analyze interdependencies between technology and capacity investment we chose a VAR model, which is a frequently applied econometric model that plays a central role in modern empirical economics to examine dynamic interdependencies among multiple time series.\(^{10}\) In a VAR model, each variable is explained by its own lags and the lags of the other variables in the model. An apparent advantage of this model originally advocated by Sims (1980) is the fact there is no requirement to fit the model into a narrow structure and specify dependent and independent variables, as all variables in the model are treated as endogenous. To illustrate how the VAR model works, we start with a simple two-equation system and then generalize it to our multi-equation setting. The structural form of a bivariate first-order VAR model can be denoted as follows:

\[
y_t = b_{10} - b_{12} y_t + y_{11} y_{t-1} + y_{12} z_{t-1} + \varepsilon_{yt} \\
z_t = b_{20} - b_{21} z_t + y_{21} y_{t-1} + y_{22} z_{t-1} + \varepsilon_{zt}
\]  

or, after collecting the variables \( z \) and \( y \) into a 2 x 1 vector \( x \)

In the Equations (1) and (2) it is assumed that both \( z_t \) as well as \( y_t \) are stationary and \( \varepsilon_{yt} \) as well as \( \varepsilon_{zt} \) represent white-noise disturbances. In its structural form, the model cannot be used to estimate the VAR system because standard estimation techniques require that the regressors are uncorrelated with the error terms. Consequently, using matrix algebra, the system is converted to the standard form:

\[
\begin{pmatrix}
1 & b_{12} \\
b_{21} & 1
\end{pmatrix}
\begin{pmatrix}
y_t \\
z_t
\end{pmatrix}
= 
\begin{pmatrix}
b_{10} \\
b_{20}
\end{pmatrix}
+ 
\begin{pmatrix}
y_{11} & y_{12} \\
y_{21} & y_{22}
\end{pmatrix}
\begin{pmatrix}
y_{t-1} \\
z_{t-1}
\end{pmatrix}
+ 
\begin{pmatrix}
\varepsilon_{yt} \\
\varepsilon_{zt}
\end{pmatrix}
\]

\( ^{10} \) For a more comprehensive review of VAR models see also Sims (1980), Lütkepohl (1988); Pesaran and Smith (1998), Christiano, Eichenbaum, and Evans (1999) among others.
\[ Bx_t = \Gamma_0 + \Gamma_1 x_{t-1} + \epsilon_t \]  

Premultiplication with \( B^{-1} \) yields

\[ x_t = A_0 + A_1 x_{t-1} + \epsilon_t \]  

where \( A_0 = B^{-1} \Gamma_0; A_1 = B^{-1} \Gamma_1; \epsilon_t = B^{-1} \epsilon_t \)

The format can be restated as

\[ y_t = a_{10} - a_{11} y_{t-1} + a_{12} z_{t-1} + \epsilon_{1t} \]  

\[ z_t = a_{20} - a_{21} y_{t-1} + a_{22} z_{t-1} + \epsilon_{1t} \]  

which represents the standard form of Equations (1) and (2). The general form of the standard VAR model can be represented as follows:

\[ x_t = \sum_{k=1}^{i} B_k x_{t-k} + \epsilon_t \]  

In Equation (1), \( x \) represents an \( n \)-dimensional vector of endogenous variables, whereas \( B \) constitutes an \( n \times n \) matrix of regression coefficients to be estimated and \( i \) represents the number of lags included in the model. Furthermore, the error term \( \epsilon_t \) is assumed to be interdependent, with a mean of zero and a constant variance. In order to construct our VAR model, we draw on prior research conducted by Henriques and Sadorsky (2008). In their work, they use a VAR analysis to examine interdependencies between technology stocks, alternative energy stocks, and oil prices. Moreover, they include the interest rate as an additional variable in their analysis. Similarly, in our model we include VC investment to operationalize (solar) technology investment and AF investment to operationalize (alternative) energy capacity investment. In contrast to the work conducted by Henriques & Sadorsky (2008), which captures
interdependencies across industrial sectors, our model captures interdependencies along the value chain within a specific technology sector, namely, the solar sector. In addition, instead of using publicly available data on stock prices, we rely upon non-public equity technology and capacity investment, which is the dominant source of finance in the solar technology sector in the period under investigation (Schock et al., 2014). As we are not using public equity market data, our model includes data on VC and AF cleantech fundraising, which accounts for the supply of funds available for technology and capacity investment. Consequently, we construct our VAR model using the following variables:

\[ VC_t = \alpha_{10} + \sum_{i=1}^{2} \alpha_{11,i} VC_{t-i} + \sum_{i=1}^{2} \alpha_{12,i} AF_{t-i} + \sum_{i=1}^{2} \alpha_{13,i} FR_{t-i} VC_{t-i} + \sum_{i=1}^{2} X_{t-i} \beta_{1,i} + e_{1t} \]  

(9)

\[ AF_t = \alpha_{20} + \sum_{i=1}^{2} \alpha_{21,i} VC_{t-i} + \sum_{i=1}^{2} \alpha_{22,i} AF_{t-i} + \sum_{i=1}^{2} \alpha_{23,i} FR_{t-i} VC_{t-i} + \sum_{i=1}^{2} X_{t-i} \beta_{2,i} + e_{2t} \]  

(10)

\[ FR_{t} = \alpha_{30} + \sum_{i=1}^{2} \alpha_{31,i} VC_{t-i} + \sum_{i=1}^{2} \alpha_{32,i} AF_{t-i} + \sum_{i=1}^{2} \alpha_{33,i} FR_{t-i} VC_{t-i} + \sum_{i=1}^{2} X_{t-i} \beta_{3,i} + e_{3t} \]  

(11)

where \( X_t = (GDP_t, FedF_t, Oil_t, FR_{AF_t}) \) is a 1 x 4 row vector of exogenous parameters and \( \beta_{k,i} \) is a 4 x 1 column vector of the corresponding parameters.

4.2 Data

For our analysis of interrelations between technology and capacity investment flows in the US solar technology sector, we utilize data collected by Bloomberg New Energy Finance (BNEF). The BNEF
database captures technology and capacity capital flows in new energy-related industries from 1996 to date.

In order to analyze whether technology drives the market or vice versa, we utilize VC investment in the solar sector to operationalize investment that drives solar technology advancement or commercialization. As discussed above, VC investment is associated with increased innovative output at the firm level as well as with increased efforts to bring new technologies and products to market. In our analysis, we use quarterly data on disclosed transaction values in millions of dollars of VC transactions in the US from 2001 to 2012 to measure investment in technology advancement and/or technology commercialization. Among the VC solar technology transactions in the database, transaction values are recorded for around 90% of the deals, which provides a good representation of VC transactions in this period.

Analogous to the use of VC investment to operationalize technology investment, we use AF investment in solar power infrastructure to operationalize investment that drives capacity for solar technology product applications. As with VC investment, we draw on quarterly data covering the disclosed transaction values of AF investment in the US in million dollars from 2001 to 2012. Unfortunately, due to the fact that many AF transactions involve confidential deals, transaction values are not disclosed for about 70% of the transactions in our sample. However, for most of these transactions, data on installed capacity were available on the basis of which the transaction values could be approximated. Thus, our

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11 An analysis of the business model of VC investment targets in the database shows, that approx. 32% of the companies are classified as technology developers whereas approx. 38% of the companies are classified as equipment manufacturers (see Appendix, Figure 8-2). We regard companies categorized as technology developers as a proxy for technology advancement and companies categorized as equipment manufacturers as a proxy for technology commercialization.

12 From a total of 483 completed VC transactions in the solar sector during the period from 2001 to 2012, transaction values are disclosed for 439 VC transactions.

13 This operationalization is consistent with recent works that use capacity additions as proxy for demand-pull policies (Peters et al., 2012: 1301).

14 We have conducted a robustness check including only the transaction values that are explicitly disclosed in the database. In principle, the results of the analysis remain unchanged.
final analysis of transaction values covers more than 90% of the total AF transactions recorded in the period being examined.\textsuperscript{15}

In our VAR analysis (Coad, 2010), we include information on 439 completed VC solar technology investments in the US in 2001 to 2012 for which the transaction value was disclosed. VC investment during the period from 2001 to 2012 totals about $6.971bn. In the case of solar capacity/market investment, we include information on 815 completed investments in solar power infrastructure from 2001 to 2012, totaling $68.181bn.

In equations (9)-(11), \textit{VC} represents the first differences of the logged transaction value of VC investments in early-stage and growth-stage solar technology companies.

Similarly, \textit{AF} represents the first differences of the logged transaction value of solar power capacity investments.

The variable \textit{FR\_VC} represent the first differences of the logged venture capital clean technology funds raised in $m. The parameters of the model are the vectors of constants $\alpha_{i0}$ as well as the coefficients $\alpha_{ijkl}$. The terms $e_{it}$ are assumed to be independently and identically distributed disturbance terms.

In addition, we control for \textit{FR\_AF}, representing asset finance fundraising activity, which captures the supply of capital deployed by capacity investors in millions of dollars.

Further, we include the gross domestic product (\textit{GDP}) in millions of dollars as a measure of general private and public investment activity, the federal funds rate (\textit{FedF}) as a percentage as a measure of the cost of capital and the oil price (\textit{Oil}) in dollars per barrel as a proxy for the cost of energy.

\textsuperscript{15} From a total of 819 completed AF transactions in solar power infrastructure from 2001 to 2012, transaction values are disclosed for 221 AF transactions. For 594 transactions with no disclosed transaction values, capacity data was available for which the transaction values could be approximated. In sum, transactions values could be obtained for 815 transactions.
4.3  Descriptive statistics

A visual inspection of our main variables, technology investment (VC) and capacity investment (AF), suggests the presence of a structural break in the time series in 2006 to 2007 (see figure 2). A separate analysis of the summary statistics for the two periods, from 2001 to 2006 as well as from 2007 to 2012, confirms this observation. In addition, as indicated by the summary statistics (see table 1), the capacity/market investment data is skewed toward the mid- to late 2000s with relatively few data points in the early 2000s. The distribution is attributable in part to the development of solar technologies over the past decade, with more advanced technologies becoming available in the mid-2000s, which allowed more large-scale field applications than in previous years. However, the main factor is the impact of the 2008 financial crisis and its consequences for technology as well as capacity/market investment. To compensate for the regime change for investors in solar caused by the financial crisis, the time series was split into two different periods: From 1Q2001 to 4Q2006 and from 1Q2007 to 4Q2012. Consequently, the split sections of the time series were standardized by using means and standard deviations and merged again to allow for a comparison of the investment flows over the entire period from 2001 to 2012.

figure 2 about here

A visual inspection of the standardized time series suggests that some of the data series used for the model are not stationary. We test whether the natural logarithms of the time series are stationary using the augmented Dickey-Fuller (ADF) test. The ADF test confirms that most of the variables exhibit a unit
root and are not stationary in levels, with the exception of the oil price. However, when first-differencing the data, we find stationary time series for all variables in our model (see Appendix, Table 8-1). Because the time series are first-difference stationary and potentially cointegrated, analyzing the VAR in levels yields consistent but potentially inefficient parameter estimates. Because of the information that is lost in the differencing process, some authors (Doan & Litterman, 1992; Sims, 1980) argue in favor of using the data in levels despite the non-stationarity. Moreover, the “loss of efficiency is considered preferable to imposing possibly incorrect restrictions on the data resulting in a mis-specified model” (Voss, 2002).

Nevertheless, the prevailing opinion on stationary data expressed by Granger and Newbold (1974), Phillips (1986) and others argues that stationary data should be used to avoid spurious regression results. Consequently, we use the stationary first-differenced time series and conduct several sensitivity and robustness checks to ensure the functionality of our model (see 5.1). Specifically, we conduct ancillary analysis to examine whether our model reacts as indicated in the literature. In addition, we also conduct the same analysis using the variables in levels. The principal results remain unchanged.

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figure 3 about here
*****************************************************************************

5 Results

The lag length included in our VAR model is based on the information criterion statistic, as suggested by Hamilton (Hamilton, 1994). Specifically, the lag length in our model has been chosen based on testing down from a maximum of 8 lags. For the initial VC-AF model, the Hannan-Quinn Information Criterion (HQC) and the Bayesian Information Criterion (BIC) suggest including a lag of 2, whereas the Akaike Information Criterion (AIC) suggests including a lag of 3 (see Appendix, Table 8-2). For the final VC-AF-FR_VC model, the results are more ambiguous: The HQC confirms the lag of 2, whereas the BIC and AIC suggest including lags of 1 and 5, respectively (see Appendix, Table 8-3). For the final model, a lag of 2 is
chosen in line with the HQC criterion, which is stable in both models and is frequently used for quarterly data (Ivanov & Kilian, 2005). Using this number of lags, the VAR inverse roots in relation to the unit root circle suggest that the model is stable (see Appendix, Figure 8-1). We also conduct a Johansen test to check for any possible cointegrating relationship between the individual variables in our model in order to analyze whether a Vector Error Correction Model (VECM) is more appropriate for our dataset. The results from the Johansen test suggest that there is no evidence of a cointegrating relationship (see Appendix, Table 8-5), therefore we proceed with our original VAR model. The results of the VAR analysis can be found in Appendix, Table 8-4, along with the presentation of the VAR inverse roots analysis (Figure 8-1). The impulse-response functions for the main variables, technology investments (d_in_VC) and capacity investments (d_in_AF) along with the supply side of technology investments (d_in_FR-VC) are presented in Figure 4 below.

In our model, an impulse to technology investment leads to an immediate response of capacity investment around quarter 2, which lasts for approximately two quarters. In particular, an impulse of one standard deviation to technology investment increases capacity/market investment for up to 0.25 standard deviations. Following the positive reaction, we observe a smaller but statistically significant negative effect around quarter 3. We attribute the negative effect to the cyclicality of capacity investment, which is also observable in the original data. In particular, the original data shows that periods of higher investment are followed by periods of lower investment. The immediate effect of technology investment on capacity/market investment at first seems counterintuitive. After all, one would expect that the development and deployment of new technologies connected with such investment demands a significant period of time. However, we measure technology investment using capital commitments by VC firms. Therefore a delayed effect of technology - VC investment - would...
suggest that following the VC investment, considerable time is required to bring the technology to the market. Clearly this is not the case here, indicating that in the solar sector VC investment was made in companies that had already developed technologies that had achieved almost market-readiness. In this respect, our research provides further support for the Innovation-First thesis rather than the VC-First thesis. Part of the reaction could also be attributable to behavioral patterns of large institutional investors, which represent the majority of solar capacity investors. In particular, VC investment activity might send signals to institutional investors, which in turn contribute capital to the same investment category.

From the literature on VC decision-making, we would also suspect that capacity investment leads to a consequent increase in technology investment, because technology investors, and specifically VC, value market size and market growth. In fact, some renowned VC investors, such as Don Valentine of Sequoia, have said that market characteristics are their number one decision-making criterion. Surprisingly, in the case of the US solar sector, an impulse to make capacity investment does not lead to an increase in technology investment: Although the impulse-response functions display a positive effect of around 0.20 at quarter 4, the effect is not statistically significant. This result suggests that solar capacity investment in the US has not generated enough market-pull effect to induce new solar technology investment. When considering the substantial amounts of capital deployed in solar capacity assets, which according to BNEF totaled around $69bn in the period 2001-2012, compared with only about $7bn in technology investment, the lack of stimulus caused by capacity investment is even more puzzling.

When comparing the characteristics (size, duration, and timing) of the response from an impulse to technology investment to the response caused by the same impulse to capacity/market investment irrespective of the statistical significance, we observe that the maximum size of the responses in both cases is comparable, around 0.20-0.25 standard deviations. For the solar sector, this means that the
maximum percentage growth in solar power capacity in one quarter that can be expected from increasing solar technology investment is around the same maximum percentage growth in solar technology investment that can be expected from increasing solar power capacity. This result is interesting, as the amount of capital deployed in capacity investment is around 10 times as large as the amount deployed in technology investment. Thus, a dollar amount invested in solar technology is able to drive a much larger dollar amount of solar capacity investment. Moreover, with a positive and significant effect of around two quarters, the persistence of growth in solar capacity following an impulse to solar technology investment is stronger than vice versa. Therefore, we conclude that the overall response caused by an increase in technology investment is more pronounced than the overall response caused by an impulse to capacity investment. The immediate positive and significant reaction of capacity investment toward an impulse to technology investment indicates that VC investors in solar technology companies are likely to pursue a rapid dissemination of their technologies in solar power field installations. In contrast, the reaction to an increase in solar capacity investment by VC investors, while not significant, is also less immediate, as indicated by the delay of around four quarters. One possible reason for the delayed response of technology investment could in part be the time lag between the original investment and disclosure of information about the investment. As stated in Chapter 4.2, around 70% of the solar power infrastructure investments do not disclose details of the deal, therefore transparency on capacity installed and hence market growth rates might not be immediately available. In addition, VC investors in solar technology might also wait for a more sustainable trend in market growth rates before committing capital.

In addition to the impulse-response analysis, we also perform Granger causality tests to examine whether all the lags of a single variable taken together have an aggregate impact on other variables in the model. This test provides further information on the interdependencies examined in the impulse-response analysis. In our model, the results of the Granger causality test provide further verification of
the inferences drawn from the impulse-response charts: Whereas technology (VC) investments can be explained by past values of technology investment as well as VC funds raised, past values of capacity investment do not contribute toward explaining the current level of technology investment. In contrast, past values of technology investment provide a significant contribution to the current level of capacity investment and, in fact, provide even more explanatory power than past values of capacity investment themselves (see Table 2). Interestingly, past values of technology investment have no significant explanatory power for funds raised for technology investment, which is somewhat surprising given the influence of VC investment on VC fundraising, which is well documented in the literature. Instead, the current level of VC fundraising is explained mainly by past values of VC fundraising. This finding indicates that the funds raised for technology investment in the solar sector were influenced more by external supply-side factors and less by the underlying performance of VC technology investment.

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Table 2 about here
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We also examine forecast error variance decompositions. This analysis provides information on the share of variance in one variable caused by the other variable(s) in the VAR model. In the case of the solar sector, technology investment explains around 18% of the variation of capacity investment after the first year, whereas capacity investment explains only around 6% of the variation of technology investment after the first year (see Table 3). The results of the forecast error variance decomposition confirm the view gained from the impulse-response analyses and the Granger causality tests: The influence of technology investment on capacity investment is comparatively large, whereas capacity investment has little impact on technology investment despite the considerable amount of capital resources committed to the solar asset finance sector.
The impulse-response function of VC toward VC provides insight on the reaction of solar technology investors on investment behavior by their peers. After an initial spike immediately following the impulse, VC solar technology investment experiences a significant subsequent decrease in the second quarter. The initial spike suggest that at the time of the impulse, other VC investors were also already in negotiations with similar companies in the sector or were part of a syndicated deal involving the same company (Dimov and Milanov, 2010). The following decrease is a normal reaction to the first impulse and is attributable to the cyclical investor behavior, which is documented in the literature and observable in the original data. After this initial decrease in solar technology investment, we consequently can observe another spike three quarters after the initial shock, which is close to being significant at the 10% level. With around 0.20 standard deviations, the size of the second spike is considerably smaller than the preceding decrease at around -0.60 standard deviations. Interestingly, the responses of VC investment to an impulse to VC investment do not support the claims of herding effects, in which other VC investors follow the investment behavior of established firms in the sector. Nevertheless, the cyclical pattern of the VC investment behavior as described in the literature is clearly visible in the impulse-response functions.\(^{16}\)

The analysis of the forecast variance decomposition also shows that around 23% of the variation in VC technology investment is explained by VC fundraising. Hence, the supply of capital for technology investors in the US is considerably more influential than the amount of solar capacity installed. Again, this result is rather intuitive, as capital resources are a prerequisite for technology investment; however, 

\(^{16}\) For more detailed information on the cyclicality of VC investments see Gompers, Kovner, Lerner, and Scharfstein (2008); Kaplan and Schoar (2005).
it also stresses the importance of the supply side in terms of capital and technology compared to the commercial demand-side characteristics of the capacity market.

5.1 Robustness checks

We also conduct robustness checks to test whether our model reacts adequately to impulses to the supply of capital funds available for technology investment. Specifically, we examine the relationship between solar technology investment by VC firms and the volume of new VC funds raised that are dedicated to this particular investment category. As VC funds raised represent the single most important source of capital for VC firms, we expect a positive response by VC solar technology investment following an impulse to VC fundraising. The results of the VAR analysis confirm our expectations: VC solar technology investment reacts positively to an impulse of VC fundraising. In particular, a one-standard-deviation impulse to VC fundraising increases VC investment by almost 0.40 standard deviations in the first two quarters after the impulse. Following the increase in VC investment in the first quarter, we observe a consequent correction, which is likely attributable to cyclical investment behavior, as stated above. The results from the impulse-response functions confirm the findings from the Granger causality test (see Table 2), that is, lags in VC fundraising activity in the clean technology sector have a significant effect on VC solar technology investment. In contrast, we find mixed evidence for the influence of solar technology investment on clean technology funds raised. The impulse-response functions display a positive and significant reaction of clean technology fundraising activity of size 0.25 around quarter 3 following an increase in technology investment. Although this result is in line with prior research on the determinants of VC fundraising activity (Cumming, Fleming, & Suchard, 2005), the Granger causality test does not confirm the findings from the impulse-response analysis. In particular, evidence from the Granger causality test shows that clean technology fundraising activity is influenced by past values of clean technology fundraising activity, but not past values of technology

\footnote{In this case, VC fundraising comprises of funds raised for VC investments in the ‘cleantech’ sector. Within the cleantech sector, a significant share of investments is dedicated to the solar technologies (Schock, von Flotow & Täube, 2014). Therefore, VC cleantech fundraising activity can serve as a proxy for capital funds available for VC firms to invest in solar technologies.}
investment. The mixed results from the two analyses are likely related to the informative content of our data. Specifically, the probability of raising a new fund is determined more by the success - that is, the internal rate of return - achieved with the past investment and less by the amount of capital committed in the past (see Gompers and Lerner (1998) for a more comprehensive analysis).

As our data is not able to capture the success of past investments, our analyses are less meaningful in this direction. Nevertheless, we can see from the impulse-response functions that VC cleantech fundraising reacts to an impulse in VC solar technology investment. Specifically, VC funds raised increase by up to 0.20 following an impulse of VC investment of one standard deviation, thereby confirming the principal conclusions in the literature. However, the fact that the reaction is not confirmed by the Granger causality test shows that our data lack a success measure component required to examine this relationship more thoroughly.

As in the relationship between the volume of solar technology investment by VC firms and the volume of new cleantech VC funds raised, we expect to find a similar link between the volume of solar power infrastructure investment and the volume of new cleantech infrastructure funds raised. However, in the case of solar power infrastructure investment or infrastructure investment in general, the relationship between the investment and the new funds raised is less clear than in the case of the VC model. In contrast to VC investment, which typically draws its capital from a fund structure, solar power infrastructure investment comes from a variety of investors, many of which do not rely on a fund structure.\(^\text{18}\) The results of the VAR analysis reflect these circumstances; following an impulse of one standard deviation to solar infrastructure fundraising, we observe an initial positive but insignificant

\(^\text{18}\) Significant amounts of solar power infrastructure investments are conducted by insurance companies, banks or government institutions all of which do not require a fund structure in order to make investments.
reaction of solar capacity investment. Conversely, there is also no statistically significant evidence that solar power infrastructure investment contributes to an increase in solar infrastructure fundraising. If anything, it shows that an impulse to solar power infrastructure investment reduces solar infrastructure funds raised in the first 3 quarters, after which the effect turns positive. However, none of the responses is statistically significant.

As supplementary analyses and robustness checks, we also investigate the impulse-response functions between other sources of finance for solar technology companies or solar power infrastructure from our model. Specifically, we test the responses of AF investment toward an impulse in corporate mergers and acquisitions (M&A), solar technology firm initial public offerings (IPOs), and public grant commitments. We find no significant responses of AF investment that go beyond an immediate, short-term effect for all cases. In the case of public grant commitments, our result is somewhat surprising, as we would expect to find a significant reaction among AF solar power infrastructure investments to this particular source of finance, as evidenced in other empirical studies. The absence of a significant reaction therefore might be attributable to our dataset, which, in the case of public grant commitments, does not include tax incentives or feed-in tariffs.

6 Discussion and Conclusion

In this paper, we examined interdependencies between technology investment and capacity investment based on data from the US solar sector for the period 2001-2012. We based our analysis on impulse-response functions, Granger causality tests, and forecast error variance decompositions using a VAR model to analyze these interdependencies.

We find that capacity investment is driven by technology investment\textsuperscript{19} whereas in the reverse, we do not find evidence for a stimulus to technology investment caused by an increase in capacity investment. In

\textsuperscript{19} Stated another way, capacity investments are Granger-caused by technology investments.
contrast to what we would expect based on the literature on VC decision-making, the results suggest that the rapidly growing solar capacity market has not significantly contributed to technology investment by VC despite the substantial capital of around $69bn spent on solar capacity in the period 2001-2012, around 10 times the amount spent on solar technology investment. As clean technology funds raised for VC investment are also substantial during the period under investigation, a potential lack of capital for technology investment in the US cannot explain this result. Instead, it is likely that other features of the solar capacity market, such as the need for a supportive government policy or the presence of large and competitive existing firms are discouraging technology investors from taking advantage of the attractive capacity market growth.

More generally, the solar PV industry is characterized by some sectoral specificities that form a boundary condition for our research, namely an industry structure with a fundamentally fragmented value chain with project developers and companies building solar farms and investors and banks engaged in asset finance (capacity investment) on the one hand and technology firms and their VC and PE investors on the other. This stems from the distinct properties of the industry’s value chain and the fact that large asset managers, such as insurances or pension funds are allowed to invest in solar farms as their return profiles meets the investors’ objectives. Thereby asset investors capture a large fraction of the value that is generated over the lifetime of solar technology through their solar parks. By inference, technology firms do not automatically benefit from scaling up installed capacity, because they cannot appropriate in later value chain phases the value they generate in the early phase(s) (Hockerts and Wüstenhagen, 2010). This can explain why asset investments do not trigger substantial technology investments as expected from VC literature and calls into question the generic argument that potential market growth drives VC investments. At most, this holds true for other industries without such highly fragmented value chains and different investor types, respectively. Based on our empirical results our findings allow the
conclusion that this relationship between capacity investment and technology investment depends on the industry-specific value chains and needs to be investigated individually.

6.1 Theoretical implications

We contribute to the literature on VC decision-making through an analysis of the endogenous relationship between VC investment and growth. Moreover, we extend the policy focus of the technology-push versus market-pull debate by investigating interdependencies between the two in an inter-temporal fashion and emphasizing a financing point-of-view. While our findings support the technology-push view, it has to be qualified by this focus on financial investment. In other words, innovation policy using market-pull mechanisms could be effective in indirectly triggering technological innovation too; however, it does not increase (private) funding for innovative technologies. Accordingly, public R&D funding continues to play a role in the innovation system.

We provide a nuanced picture of (private) financing of innovation drivers in the solar industry. We find that financing of market pull-oriented capacity invested does not trigger future technology investment (cf. Hargadon & Kenney, 2012). By focusing on private financing of market capacity, our findings complement those of Hoppmann et al. (2013) who showed that policy-induced market growth does not lead to future exploration of less mature technologies; their finding of a shift to more exploitation of mature, i.e. market-ready technologies provides some explanation for our results.

Our analysis shows that (private) technology investment not only leads to technological innovation and additional investment by other technology investors but also has a measurable effect on capacity growth.20 Through our analysis, we found quantitative evidence for the impact of VC investment on technology commercialization and hence market growth complementary to commonly used patent data (Costantini et al., 2015).

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20 As noted in the data section, we use capacity investments as a proxy for capacity growth. The real effect of technology investments on capacity in MW is likely to be even larger due to solar panel efficiency gains with more MW gained per $ invested.
In addition, we also add to the literature on VC decision-making and investment behavior, specifically, the VC-First vs. the Innovation-First debate (Bertoni et al., 2011; Croce et al., 2013; Rosenbusch et al., 2013; Aggarwal et al., 2015). In particular, the immediate response of capacity investment to an impulse to technology investment indicates that the target firms in most cases already exhibit technologies that are near market-readiness and use VC funding to further develop and commercialize their technologies (cf. Hoppmann et al., 2013). Consequently, our results support the Innovation-First thesis.

Interestingly, although investment activity by corporate investors, as measured by the value of corporate M&A transactions in the solar technology sector, exhibits a positive and significant impact on solar capacity investment in the short term, there is no evidence of a medium- or long-term impact on solar capacity investment. We attribute at least some of the stronger medium-term impact of VC investment on solar power infrastructure investment to the more aggressive commercialization of solar technologies by VC investors than by corporate investors (Kortum and Lerner 2000).

6.2 Managerial and Policy Implications

In addition to contributing to the literature, our research also has practical implications. Specifically, the strong cyclicality between VC investment and capacity investment can create imbalances in the supply of capital for solar technology firms: strong variations between periods with an abundance of capital and periods with a relative shortage of capital. This cyclicality should not be disregarded by firms that are considering VC financing as an alternative.

The evidence from the impulse-response analysis and the Granger causality tests also raises questions about the adequacy of policy measures, which aim to disseminate certain technologies by facilitating market growth. In the case of the solar sector, one such measure being the introduction of feed-in tariffs, which are designed primarily to increase capacity investment by providing a reliable income stream for capacity investors (e.g. Taylor, 2008; Hoppmann et al., 2013; Hoppmann et al., 2014). The introduction of feed-in tariffs can be interpreted as an impulse to solar capacity investment, which in the
case of the US, have no significant impact on solar technology investment as evidenced by the results of our impulse-response analysis. In this regard, there is no evidence of a self-reinforcing investment cycle between technology and capacity investment in the solar sector, as is the case in other industrial sectors. Moreover, the positive response of capacity investment to an impulse to technology investment is not sustainable over the long term, thus, renewed investment activity is required after around 4 to 5 quarters to maintain the momentum.

Overall, our results show that technology investment has greater ability than capacity investment to drive the general market: The response of capacity investment caused by an impulse to technology investment is statistically significant and stronger (approx. 0.25) than the response of technology investment to an impulse to capacity investment (approx. 0.20), which lacks statistical significance. The results of the Granger causality test as well as the forecast error variance decomposition reinforce the evidence from the impulse-response analysis: In the latter, technology investment explains around 18% of the variance of capacity investment, whereas capacity investment explains only around 6% of the variance of technology investment. This finding is interesting, as technology investment is “cheaper” than capacity investment by a factor of approximately 10 but has a comparatively larger effect. This means that a dollar amount invested in solar technologies has greater leverage on overall solar sector development than the same dollar amount invested in solar capacity. From a policy perspective, this raises the question of whether greater emphasis on measures that incentivize technology investment is more efficient in fostering certain industries or sectors than those that incentivize capacity investment. The results of our analysis support this proposition.

One reason for this situation could be the lack of capital resources available to technology investors; however, the level of funds raised for clean technology VC investment does not suggest capital shortages
for US VC firms in this regard. Another reason could be that despite the rapid expansion of the solar market, other features of the market have limited the market-pull effect toward technology investment. Among the reasons could be a dependence on an appreciative government stance toward this type of energy through ongoing support (e.g. tax incentives) or the presence of large and aggressive existing firms. The former creates insecurity as to whether the market growth will continue in the same pace in the future, whereas the latter limit the profits to be gained in a competitive large and fast-growing market.

6.3 Limitations and future research

Like all social science this study has some limitations. First, we limit our analysis to one sector in one country. The sector-specific context has some bearing on the generalizability of our findings. In the solar industry we have a “discontinuation” of the value chain in the sense that technology-developing and manufacturing firms are not necessarily also installers of capacity (Hockerts & Wüstenhagen, 2010). This modularization of the value chain allows asset investors and banks to invest in capacity (solar farms), which never could invest equivalent volumes into (technology) firms. Thus, our results are only transferable to other industries with similarly fragmented structures, possibly in other renewable energy sectors. Admittedly, there was a strong influence on the global market of Chinese investment (and production) since the mid 2000s as a reaction to the German FIT (Hoppmann et al., 2014). Unfortunately, Chinese data are not available long and reliably enough to include them in our longitudinal analysis. With more robust international investment data an analysis of financial interdependencies should be possible in the future. Moreover, we can only speculate about the impact of policy-induced effects on capacity investment. In this kind of quantitative analysis it is difficult to include qualitative data on certain policy measures (cf. Polzin et al., 2015). A possible avenue of further research could investigate the absence of a significant response of technology investment to an impulse to capacity investment as indicated by

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21 According to BNEF, around $12bn of clean technology VC funds were raised during the period of 2001 to 2012.
both the impulse-response analysis and the Granger causality test. In particular, it would be interesting
to pinpoint the reasons VC technology investors in the US have not been attracted to the rapidly
expanding solar capacity market. Moreover, future research could examine the interrelation between
solar capacity investment and policy formation and implementation in the US as well as for other
countries, which have different policy regimes. From empirical evidence and other findings in the
literature, we would expect to find a significant response by solar capacity investment to impulses from
policy through the initiation of tax benefits and feed-in tariffs, which we were not able to test with our
data. Researching the direct connection between policy measures and capacity investment along with
the absence of a response by technology investment to capacity investment would thereby provide a
quantitative link between policies designed to foster end-user markets and technology investment
serving this particular market (Polzin et al., 2015; Criscuolo & Menon, 2015). In addition, it would allow
the approximation of effects of certain market-related measures among companies further down the
technological value chain. In this context, it might also be interesting to examine the effect of capacity
investment on capital flows at more mature technology companies. In our analysis, we focused attention
on investment by VC firms, which predominantly invest in companies that are younger, smaller, and less
established than other firms. By extending the analysis to later-stage PE investment in solar
manufacturers, we would be able to differentiate between the effects of capacity growth on early-stage
technology and later-stage manufacturing investment. In fact, one reason for the absence of a significant
effect by capacity investment on technology investment might be the characteristics of the solar value
chain: Specifically, technical know-how owners such as solar equipment manufacturers further up the
value chain might absorb most of the benefits from capacity growth. Therefore, future research could
also aim to differentiate the effect of capacity investment on different parts of the solar value chain.
Another limitation, stemming from research design, is the fact that we use VC as a proxy for technology
investment. Thereby this study is biased towards the technology-push investments related to small
firms. Including larger firms might change the results because they could be active in different phases of
the technology value chain. However, Kortum and Lerner (2000) find that $1 of VC has the same impact on innovation as $3 of corporate R&D, hence this bias should have relatively small consequences.\(^{22}\)

While this can be seen as valid focus on entrepreneurial financing, it is also biased to one type of financing, namely VC, which has been shown as substitute for bank loans (Berger and Schaeck 2011); hence by excluding start-up loans we might underestimate the effect of asset financing on technology-push investments. Analogously, our measure of market-pull is skewed towards large-scale capacity deployment in solar parks as opposed to small-scale homeowners’ rooftop installations. However, this should not fundamentally change our results either, as technology developers are not able to appropriate profits from such capacity additions. Finally, another avenue of further research could extend the analysis to industries outside the solar sector. Extending the analysis to other sectors that exhibit similar technology-capacity interdependencies, such as the semiconductor industry or the wind industry, would provide evidence for the generalizability of our results.

\(^{22}\) The findings seem to hold for countries outside the US or common law countries in general as evidence from the German market shows. In particular, Tyková (2000) provides evidence that firms in Germany also exhibit a higher number of patent issues following the investment of a VC firm. In addition, case study analysis of VC-backed companies in the UK suggests that VC investment activity is associated with incremental innovation as well as strategic innovation (Bruining & Wright, 2008). Still, according to evidence from 21 European countries, the magnitude of the contribution of VC to innovative output is not uniform across countries. While generally finding weaker support for the efficiency of VC investments compared to corporate R&D investments, Popov and Roosenboom (2012) find that the impact of VC on innovative output is relatively stronger in countries that exhibit a VC friendly regulatory framework.
7 Table of references


Bruining, H., & Wright, M (2008). Entrepreneurial Orientation in Management Buy-Outs and the Contribution of Venture Capital. In M. Wright & H. Bruining (Eds.),


Figure 1: Solar technology value chain (stylized)
Figure 2: Original time series for main variables
Figure 3: Standardized and first-differenced time series for main variables
Figure 4: Impulse-response functions for VC-AF-FR_VC model (technology and capacity investments)
Figure 5: Impulse-response functions for VC and FR_VC (technology investments and funds available for technology investments)
### Table 1: Quarterly summary statistics for main variables in $m$

<table>
<thead>
<tr>
<th>Period from 2001-2006</th>
<th>Mean</th>
<th>Standard deviation</th>
<th>25th percentile</th>
<th>50th percentile</th>
<th>75th percentile</th>
</tr>
</thead>
<tbody>
<tr>
<td>VC</td>
<td>21.84</td>
<td>30.15</td>
<td>0.75</td>
<td>11.25</td>
<td>34.16</td>
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<tr>
<td>AF</td>
<td>53.68</td>
<td>153.47</td>
<td>4.49</td>
<td>11.91</td>
<td>32.83</td>
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<tr>
<td>FR-VC</td>
<td>260.38</td>
<td>560.30</td>
<td>0.00</td>
<td>53.00</td>
<td>213.50</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Period from 2007-2012</th>
<th>Mean</th>
<th>Standard deviation</th>
<th>25th percentile</th>
<th>50th percentile</th>
<th>75th percentile</th>
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<tbody>
<tr>
<td>VC</td>
<td>268.60</td>
<td>149.36</td>
<td>160.90</td>
<td>245.20</td>
<td>326.52</td>
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<tr>
<td>AF</td>
<td>2,787.19</td>
<td>3,648.54</td>
<td>521.18</td>
<td>1,568.23</td>
<td>3,337.96</td>
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<tr>
<td>FR-VC</td>
<td>247.43</td>
<td>638.91</td>
<td>0.00</td>
<td>0.00</td>
<td>145.00</td>
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</table>

### Table 2: Results of Granger causality test for VC-AF-FR_VC model

<table>
<thead>
<tr>
<th>Joint F-test</th>
<th>Equation 1: d_ln_VC</th>
<th>Equation 2: d_ln_AF</th>
<th>Equation 3: d_ln_FR-VC</th>
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</thead>
<tbody>
<tr>
<td>Test statistic</td>
<td>p-Value</td>
<td>Test statistic</td>
<td>p-Value</td>
</tr>
<tr>
<td>All lags of d_ln_VC</td>
<td>F(2, 26) = 27.497 [0.0000]</td>
<td>F(2, 26) = 3.2838 [0.0535]</td>
<td>F(2, 26) = 1.7510 [0.1935]</td>
</tr>
<tr>
<td>All lags of d_ln_AF</td>
<td>F(2, 26) = 2.0129 [0.1539]</td>
<td>F(2, 26) = 2.5282 [0.0992]</td>
<td>F(2, 26) = 0.13887 [0.8710]</td>
</tr>
<tr>
<td>All lags of d_ln_FR_VC</td>
<td>F(2, 26) = 5.7099 [0.0088]</td>
<td>F(2, 26) = 0.36309 [0.6990]</td>
<td>F(2, 26) = 6.6201 [0.0047]</td>
</tr>
<tr>
<td>All vars, lag 2</td>
<td>F(3, 26) = 9.8594 [0.0002]</td>
<td>F(3, 26) = 1.0555 [0.3849]</td>
<td>F(3, 26) = 1.2132 [0.3247]</td>
</tr>
</tbody>
</table>

### Table 3: Forecast error variance decomposition

<table>
<thead>
<tr>
<th>Decomposition of variance for d_ln_VC</th>
<th>Decomposition of variance for d_ln_AF</th>
<th>Decomposition of variance for d_ln_FR-VC</th>
</tr>
</thead>
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<tr>
<td>period</td>
<td>std. error</td>
<td>d_ln_VC</td>
</tr>
<tr>
<td>1</td>
<td>0.575396</td>
<td>100</td>
</tr>
<tr>
<td>2</td>
<td>0.910627</td>
<td>85.3556</td>
</tr>
<tr>
<td>3</td>
<td>0.991594</td>
<td>75.5486</td>
</tr>
<tr>
<td>4</td>
<td>1.01932</td>
<td>72.9793</td>
</tr>
<tr>
<td>5</td>
<td>1.03746</td>
<td>71.845</td>
</tr>
<tr>
<td>10</td>
<td>1.04345</td>
<td>71.2141</td>
</tr>
<tr>
<td>15</td>
<td>1.04357</td>
<td>71.205</td>
</tr>
<tr>
<td>20</td>
<td>1.04357</td>
<td>71.2049</td>
</tr>
</tbody>
</table>
8 Appendix

Table 8-1: Results of ADF-test for standardized variables

<table>
<thead>
<tr>
<th>Variable</th>
<th>p-value With constant</th>
<th>p-value With constant and trend</th>
<th>Null-Hypotheses of non-stationarity</th>
</tr>
</thead>
<tbody>
<tr>
<td>ln_VC</td>
<td>0.2756</td>
<td>0.8119</td>
<td>Not rejected</td>
</tr>
<tr>
<td>d_ln_VC</td>
<td>1.847e-018</td>
<td>2.281e-019</td>
<td>Rejected</td>
</tr>
<tr>
<td>ln_AF</td>
<td>0.1016</td>
<td>0.3518</td>
<td>Not rejected</td>
</tr>
<tr>
<td>d_ln_AF</td>
<td>4.031e-008</td>
<td>5.033e-007</td>
<td>Rejected</td>
</tr>
<tr>
<td>ln_FR_VC</td>
<td>0.8341</td>
<td>0.9956</td>
<td>Not rejected</td>
</tr>
<tr>
<td>d_ln_FR_VC</td>
<td>1.646e-009</td>
<td>2.339e-008</td>
<td>Rejected</td>
</tr>
<tr>
<td>ln_FR_AF</td>
<td>0.4835</td>
<td>0.9494</td>
<td>Not rejected</td>
</tr>
<tr>
<td>d_FR_AF</td>
<td>2.403e-011</td>
<td>1.414e-010</td>
<td>Rejected</td>
</tr>
<tr>
<td>Oil</td>
<td>0.05779</td>
<td>0.6873</td>
<td>Rejected</td>
</tr>
<tr>
<td>d_Oil</td>
<td>2.084e-007</td>
<td>2.836e-006</td>
<td>Rejected</td>
</tr>
<tr>
<td>FedF</td>
<td>0.3001</td>
<td>0.6196</td>
<td>Not rejected</td>
</tr>
<tr>
<td>d_FedF</td>
<td>0.01755</td>
<td>0.08897</td>
<td>Rejected</td>
</tr>
<tr>
<td>sq_GDP</td>
<td>0.1105</td>
<td>0.2879</td>
<td>Not rejected</td>
</tr>
<tr>
<td>d_sq_GDP</td>
<td>0.007883</td>
<td>0.0249</td>
<td>Rejected</td>
</tr>
</tbody>
</table>

Table 8-2: VC-AF model lag selection

VAR system, maximum lag order 8

<table>
<thead>
<tr>
<th>lags</th>
<th>loglik</th>
<th>p(LR)</th>
<th>AIC</th>
<th>BIC</th>
<th>HQC</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>-103.52981</td>
<td>6.129734</td>
<td>6.812221</td>
<td>6.374604</td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>-91.47834</td>
<td>0.00008</td>
<td>5.716838</td>
<td>6.569947*</td>
<td>6.02926*</td>
</tr>
<tr>
<td>3</td>
<td>-87.05458</td>
<td>0.06503</td>
<td>5.695106*</td>
<td>6.718837</td>
<td>6.062412</td>
</tr>
<tr>
<td>4</td>
<td>-85.75147</td>
<td>0.62572</td>
<td>5.833408</td>
<td>7.02776</td>
<td>6.261932</td>
</tr>
<tr>
<td>5</td>
<td>-80.89247</td>
<td>0.04546</td>
<td>5.789358</td>
<td>7.154331</td>
<td>6.279098</td>
</tr>
<tr>
<td>6</td>
<td>-80.21039</td>
<td>0.8504</td>
<td>5.959507</td>
<td>7.495103</td>
<td>6.510466</td>
</tr>
<tr>
<td>7</td>
<td>-77.31452</td>
<td>0.21525</td>
<td>6.016129</td>
<td>7.722346</td>
<td>6.628305</td>
</tr>
<tr>
<td>8</td>
<td>-75.18986</td>
<td>0.37331</td>
<td>6.1123</td>
<td>7.989139</td>
<td>6.785694</td>
</tr>
</tbody>
</table>

The asterisks below indicate the best (that is, minimized) values of the respective information criteria, AIC = Akaike criterion, BIC = Schwarz Bayesian criterion and HQC = Hannan-Quinn criterion.
Table 8-3: VC-AF-FR_VC model lag selection

VAR system, maximum lag order 8

<table>
<thead>
<tr>
<th>lags</th>
<th>loglik</th>
<th>p(LR)</th>
<th>AIC</th>
<th>BIC</th>
<th>HQC</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>-155.96975</td>
<td>9.229218</td>
<td>10.252948*</td>
<td>9.596523</td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>-141.56279</td>
<td>0.0007</td>
<td>8.951938</td>
<td>10.359567</td>
<td>9.456983*</td>
</tr>
<tr>
<td>3</td>
<td>-133.56182</td>
<td>0.06684</td>
<td>9.00317</td>
<td>10.794698</td>
<td>9.645955</td>
</tr>
<tr>
<td>4</td>
<td>-125.11362</td>
<td>0.05036</td>
<td>9.031468</td>
<td>11.206895</td>
<td>9.811992</td>
</tr>
<tr>
<td>5</td>
<td>-109.30393</td>
<td>0.00023</td>
<td>8.682253*</td>
<td>11.241579</td>
<td>9.600517</td>
</tr>
<tr>
<td>6</td>
<td>-103.81292</td>
<td>0.27694</td>
<td>8.862201</td>
<td>11.805425</td>
<td>9.918205</td>
</tr>
<tr>
<td>7</td>
<td>-92.20424</td>
<td>0.00573</td>
<td>8.728422</td>
<td>12.055546</td>
<td>9.922166</td>
</tr>
<tr>
<td>8</td>
<td>-84.1866</td>
<td>0.06615</td>
<td>8.7788</td>
<td>12.489822</td>
<td>10.110283</td>
</tr>
</tbody>
</table>

The asterisks below indicate the best (that is, minimized) values of the respective information criteria, AIC = Akaike criterion, BIC = Schwarz Bayesian criterion and HQC = Hannan-Quinn criterion.
Table 8-4: VC-AF-FR_VC model VAR analysis

VAR system, lag order 2  
OLS estimates, observations 2001:4-2012:4, (T = 45)  
Log-likelihood = -136.85969  
Determinant of covariance matrix = 0.087950748  
AIC = 8.6160  
BIC = 10.9044  
HQC = 9.4691  
Portmanteau test: LB(11) = 92.6093, df = 81 [0.1778]

Equation 1: d\_ln\_VC

<table>
<thead>
<tr>
<th>coefficient</th>
<th>std. error</th>
<th>t-ratio</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>const</td>
<td>-0.0149792</td>
<td>0.116743</td>
<td>-0.1283</td>
</tr>
<tr>
<td>d_ln_VC_1</td>
<td>-0.937961</td>
<td>0.127585</td>
<td>-7.352</td>
</tr>
<tr>
<td>d_ln_VC_2</td>
<td>-0.675998</td>
<td>0.130104</td>
<td>-5.1960</td>
</tr>
<tr>
<td>d_ln_AF_1</td>
<td>-0.0283547</td>
<td>0.158862</td>
<td>-0.1785</td>
</tr>
<tr>
<td>d_ln_AF_2</td>
<td>-0.293985</td>
<td>0.150051</td>
<td>-1.9590</td>
</tr>
<tr>
<td>d_ln_FR_VC_1</td>
<td>0.417041</td>
<td>0.123437</td>
<td>3.3790</td>
</tr>
<tr>
<td>d_ln_FR_VC_2</td>
<td>0.232492</td>
<td>0.118289</td>
<td>1.9650</td>
</tr>
<tr>
<td>d_Oil</td>
<td>0.206759</td>
<td>0.240614</td>
<td>0.8593</td>
</tr>
<tr>
<td>d_Oil_1</td>
<td>0.582076</td>
<td>0.254611</td>
<td>2.2860</td>
</tr>
<tr>
<td>d_Oil_2</td>
<td>0.087657</td>
<td>0.263401</td>
<td>0.3328</td>
</tr>
<tr>
<td>d_FedF</td>
<td>0.218745</td>
<td>0.713371</td>
<td>0.3066</td>
</tr>
<tr>
<td>d_FedF_1</td>
<td>1.02302</td>
<td>0.864834</td>
<td>1.1830</td>
</tr>
<tr>
<td>d_FedF_2</td>
<td>-1.4268</td>
<td>0.719007</td>
<td>-1.984</td>
</tr>
<tr>
<td>d_sq_GDP</td>
<td>0.14007</td>
<td>0.314204</td>
<td>0.4458</td>
</tr>
<tr>
<td>d_sq_GDP_1</td>
<td>-0.443007</td>
<td>0.384466</td>
<td>-1.152</td>
</tr>
<tr>
<td>d_sq_GDP_2</td>
<td>0.0796206</td>
<td>0.342708</td>
<td>0.2323</td>
</tr>
<tr>
<td>d_ln_FR_AF</td>
<td>0.0656962</td>
<td>0.148470</td>
<td>0.4425</td>
</tr>
<tr>
<td>d_ln_FR_AF_1</td>
<td>0.0623512</td>
<td>0.183353</td>
<td>0.3401</td>
</tr>
<tr>
<td>d_ln_FR_AF_2</td>
<td>0.146307</td>
<td>0.152860</td>
<td>0.9571</td>
</tr>
</tbody>
</table>

Mean dependent var -0.049275  
S.D. dependent var 1.34485  
Sum squared resid 14.89862  
S.E. of regression 0.756983  
R-squared 0.812681  
Adjusted R-squared 0.682999  
F(18, 26) 6.26761  
P-value (F) 0.00016  
Durbin-Watson 2.361004  

F-tests of zero restrictions:

All lags of d\_ln\_VC F(2, 26) = 27.497 [0.0000]  
All lags of d\_ln\_AF F(2, 26) = 2.0129 [0.1539]  
All lags of d\_ln\_FR\_VC F(2, 26) = 5.7099 [0.0088]  
All vars, lag 2 F(3, 26) = 9.8594 [0.0002]
Equation 2: \( d_{\text{ln}_A F} \)

<table>
<thead>
<tr>
<th>Term</th>
<th>Coefficient</th>
<th>Std. Error</th>
<th>t-ratio</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>const</td>
<td>0.0377469</td>
<td>0.12689</td>
<td>0.2975</td>
<td>0.7685</td>
</tr>
<tr>
<td>( d_{\text{ln}_V C} )</td>
<td>0.355278</td>
<td>0.13868</td>
<td>2.5619</td>
<td>0.0166  **</td>
</tr>
<tr>
<td>( d_{\text{ln}_A F} )</td>
<td>-0.388031</td>
<td>0.17267</td>
<td>-2.2472</td>
<td>0.0333  **</td>
</tr>
<tr>
<td>( d_{\text{ln}_F R\text{VC}} )</td>
<td>-0.111453</td>
<td>0.13417</td>
<td>-0.8307</td>
<td>0.4137</td>
</tr>
<tr>
<td>( d_{\text{ln}_F R\text{VC}} )</td>
<td>-0.0835076</td>
<td>0.12857</td>
<td>-0.6495</td>
<td>0.5217</td>
</tr>
<tr>
<td>( d_{\text{O il}} )</td>
<td>0.10923</td>
<td>0.26153</td>
<td>0.4177</td>
<td>0.6796</td>
</tr>
<tr>
<td>( d_{\text{O il}} )</td>
<td>0.163245</td>
<td>0.27674</td>
<td>0.5899</td>
<td>0.5604</td>
</tr>
<tr>
<td>( d_{\text{O il}} )</td>
<td>-0.34967</td>
<td>0.28630</td>
<td>-1.2210</td>
<td>0.2329</td>
</tr>
<tr>
<td>( d_{\text{F edF}} )</td>
<td>1.78452</td>
<td>0.77538</td>
<td>2.3010</td>
<td>0.0296  **</td>
</tr>
<tr>
<td>( d_{\text{F edF}} )</td>
<td>-1.08601</td>
<td>0.94001</td>
<td>-1.1550</td>
<td>0.2585</td>
</tr>
<tr>
<td>( d_{\text{sq}_G D P} )</td>
<td>-0.844498</td>
<td>0.78151</td>
<td>-1.0810</td>
<td>0.2898</td>
</tr>
<tr>
<td>( d_{\text{sq}_G D P} )</td>
<td>0.740138</td>
<td>0.34152</td>
<td>2.1670</td>
<td>0.0396  **</td>
</tr>
<tr>
<td>( d_{\text{sq}_G D P} )</td>
<td>-1.0311</td>
<td>0.41789</td>
<td>-2.4670</td>
<td>0.0205  **</td>
</tr>
<tr>
<td>( d_{\text{sq}_G D P} )</td>
<td>0.149896</td>
<td>0.37250</td>
<td>0.4024</td>
<td>0.6907</td>
</tr>
<tr>
<td>( d_{\text{ln}_F R\text{AF}} )</td>
<td>-0.155868</td>
<td>0.16138</td>
<td>-0.9659</td>
<td>0.3430</td>
</tr>
<tr>
<td>( d_{\text{ln}_F R\text{AF}} )</td>
<td>-0.0149806</td>
<td>0.19929</td>
<td>-0.0751</td>
<td>0.9407</td>
</tr>
<tr>
<td>( d_{\text{ln}_F R\text{AF}} )</td>
<td>0.192118</td>
<td>0.16615</td>
<td>1.1563</td>
<td>0.2581</td>
</tr>
</tbody>
</table>

Mean dependent var 0.065526  S.D. dependent var 0.965697
Sum squared resid 17.60129  S.E. of regression 0.822784
R-squared 0.571047  Adjusted R-squared 0.274079
F(18, 26) 1.922926  P-value (F) 0.062559
rho -0.165272  Durbin-Watson 2.281423

F-tests of zero restrictions:

<table>
<thead>
<tr>
<th>Restrictions</th>
<th>F(2, 26)</th>
<th>P-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>All lags of ( d_{\text{ln}_V C} )</td>
<td>3.2838</td>
<td>0.0535</td>
</tr>
<tr>
<td>All lags of ( d_{\text{ln}_A F} )</td>
<td>2.5282</td>
<td>0.0992</td>
</tr>
<tr>
<td>All lags of ( d_{\text{ln}_F R\text{VC}} )</td>
<td>0.36309</td>
<td>0.6990</td>
</tr>
<tr>
<td>All vars, lag 2</td>
<td>1.0555</td>
<td>0.3849</td>
</tr>
</tbody>
</table>
Equation 3: $d_{\ln FR\_VC}$

<table>
<thead>
<tr>
<th>coefficient</th>
<th>std. error</th>
<th>t-ratio</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>const</td>
<td>-0.0189076</td>
<td>0.17276</td>
<td>-0.1094</td>
</tr>
<tr>
<td>$d_{\ln VC_1}$</td>
<td>-0.0480205</td>
<td>0.18880</td>
<td>-0.2543</td>
</tr>
<tr>
<td>$d_{\ln VC_2}$</td>
<td>-0.314746</td>
<td>0.19253</td>
<td>-1.6350</td>
</tr>
<tr>
<td>$d_{\ln AF_1}$</td>
<td>0.123136</td>
<td>0.23509</td>
<td>0.5238</td>
</tr>
<tr>
<td>$d_{\ln AF_2}$</td>
<td>0.0227519</td>
<td>0.22205</td>
<td>0.1025</td>
</tr>
<tr>
<td>$d_{\ln FR_VC_1}$</td>
<td>-0.576513</td>
<td>0.18267</td>
<td>-3.1560</td>
</tr>
<tr>
<td>$d_{\ln FR_VC_2}$</td>
<td>-0.0768173</td>
<td>0.17505</td>
<td>-0.4388</td>
</tr>
<tr>
<td>d_Oil</td>
<td>-0.0705723</td>
<td>0.35607</td>
<td>-0.1982</td>
</tr>
<tr>
<td>d_Oil_1</td>
<td>0.412293</td>
<td>0.37678</td>
<td>1.0940</td>
</tr>
<tr>
<td>d_Oil_2</td>
<td>-0.0200171</td>
<td>0.38979</td>
<td>-0.0514</td>
</tr>
<tr>
<td>d_FedF</td>
<td>-0.475000</td>
<td>1.05566</td>
<td>-0.4500</td>
</tr>
<tr>
<td>d_FedF_1</td>
<td>0.657220</td>
<td>1.27980</td>
<td>0.5135</td>
</tr>
<tr>
<td>d_FedF_2</td>
<td>0.291984</td>
<td>1.06400</td>
<td>0.2744</td>
</tr>
<tr>
<td>d_sq_GDP</td>
<td>0.0622078</td>
<td>0.46497</td>
<td>0.1338</td>
</tr>
<tr>
<td>d_sq_GDP_1</td>
<td>-0.491805</td>
<td>0.56894</td>
<td>-0.8644</td>
</tr>
<tr>
<td>d_sq_GDP_2</td>
<td>0.242849</td>
<td>0.50715</td>
<td>0.4789</td>
</tr>
<tr>
<td>d_dln_FR_AF</td>
<td>-0.0136123</td>
<td>0.21971</td>
<td>-0.6020</td>
</tr>
<tr>
<td>d_dln_FR_AF_1</td>
<td>-0.306455</td>
<td>0.27133</td>
<td>-1.1290</td>
</tr>
<tr>
<td>d_dln_FR_AF_2</td>
<td>-0.0535503</td>
<td>0.22621</td>
<td>-0.2367</td>
</tr>
</tbody>
</table>

Mean dependent var -0.031643  S.D. dependent var 1.297772
Sum squared resid 32.62617  S.E. of regression 1.120202
R-squared 0.559732  Adjusted R-squared 0.254932
F(18, 26) 1.836388  P-value (F) 0.076760
rho -0.017229  Durbin-Watson 2.026276

F-tests of zero restrictions:

- All lags of $d_{\ln VC}$: $F(2, 26) = 1.751$ [0.1935]
- All lags of $d_{\ln AF}$: $F(2, 26) = 0.13887$ [0.8710]
- All lags of $d_{\ln FR\_VC}$: $F(2, 26) = 6.6201$ [0.0047]
- All vars, lag 2: $F(3, 26) = 1.2132$ [0.3247]

For the system as a whole:

- Null hypothesis: the longest lag is 1
- Alternative hypothesis: the longest lag is 2
- Likelihood ratio test: Chi-square (9) = 44.3921 [0.0000]

Comparison of information criteria:

- Lag order 2: AIC = 8.61599, BIC = 10.9044, HQC = 9.46909
Table 8-5: Results for Johansen cointegration test for VC-AF-FR_VC model

Johansen test:
Number of equations = 3
Lag order = 2
Estimation period: 2001:4 - 2012:4 (T = 45)
Case 3: Unrestricted constant
Exogenous regressor(s): d_Oil d_FedF d_sq_GDP d_ln_FR_AF
Log-likelihood = -42.5664 (including constant term: -170.271)

Cointegration tests, ignoring exogenous variables

<table>
<thead>
<tr>
<th>Rank</th>
<th>Eigenvalue</th>
<th>Trace test</th>
<th>p-value</th>
<th>Lmax test</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>0.78447</td>
<td>137.44</td>
<td>[0.0000]</td>
<td>69.059</td>
<td>[0.0000]</td>
</tr>
<tr>
<td>1</td>
<td>0.56423</td>
<td>68.381</td>
<td>[0.0000]</td>
<td>37.379</td>
<td>[0.0000]</td>
</tr>
<tr>
<td>2</td>
<td>0.49789</td>
<td>31.002</td>
<td>[0.0000]</td>
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Corrected for sample size (df = 34)

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<tr>
<td>2</td>
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Note: in general, the test statistic s above are valid only in the absence of additional regressors.

eigenvalue 0.78447 0.56423 0.49789

beta (cointegrating vectors)

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<th>d_ln_FR_VC</th>
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alpha (adjustment vectors)

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<td>d_ln_AF</td>
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renormalized beta

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renormalized alpha

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<tr>
<td>d_ln_AF</td>
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long-run matrix (alpha * beta')

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</table>
Figure 8-1: VC-AF-FR_VC model VAR inverse unit roots in relation to the unit circle

Figure 8-2: Business model of VC investment targets in % of transaction value in $m
Figure 8-3: Solar technology value chain (detailed)
001 - Exploring Europe’s R&D deficit relative to the US: differences in the rates of return to R&D of young leading R&D firms - Michele Cincera and Reinhilde Veugelers

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