Sluggish Private Investment in Japan’s Lost Decade: Mixed Frequency Vector Autoregression Approach*

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Abstract

It is well known that sluggish private investment plagued the Japanese macroeconomy during the Lost Decade. Previous empirical papers have not reached a clear consensus on what caused the investment slowdown. This paper sheds new light on this issue by fitting a mixed frequency vector autoregressive model to monthly stock prices, quarterly bank loans, firm profit, and private investment. Monthly stock prices explain as much as 50.7% of the long-run forecast error variance of investment. Moreover, we reveal a spiral of declining stock prices, profit, and investment. Finally, the stagnation of bank loans is a consequence of declined stock prices, and it is not a cause of declined investment.

Keywords: Japan’s Lost Decade, Mixed Data Sampling (MIDAS), mixed frequency vector autoregression (MF-VAR), private investment.

JEL Classification: C32, E22, E44.

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1 Introduction

Japan experienced more than a decade of economic stagnation, which is called the Lost Decade or sometimes the Lost Two Decades, after the stock market bubble burst in 1990. It is well known that the slump of private non-residential investment plagued the Japanese economy in that period. Macroeconomists tried to explain what caused the investment slump, ending up with mixed results. Was the sluggish investment caused by firm-specific factors, bank-specific factors, or some other macroeconomic factors affecting both firms and banks? Firm-specific factors include a decrease in current or expected future profit that discourages firms from investing. Bank-specific factors, also called credit crunch, include a tougher lending attitude of banks due to their worse financial conditions.

Typically, previous researchers test for the relevance of bank-specific factors in two steps. First, they investigate the impact of banks’ financial conditions on their attitude to lend money to private firms. Second, researchers estimate the sensitivity of corporate investment functions to the lending attitude of banks.

For the first step, most researchers have found a significant impact of banks’ financial conditions on their lending attitude in 1997-1998, when Japanese banks were facing particularly serious situations. Empirical results for other periods are mixed, however. Ito and Sasaki (2002) and Dell’Ariccia (2003) argue that declined bank lending in the early 1990s and early 2000s was indeed caused by banks’ financial conditions. Horiuchi and Shimizu (1998) and Woo (2003), in contrast, find that the worse financial conditions of banks did not cause less bank lending in early 1990s.

For the second step, Motonishi and Yoshikawa (1999) find that the investment slump in 1997-1998 was likely attributable to the tougher sentiment of money lenders, a supportive evidence for the bank-specific factor. Ogawa (2003) obtains similar results for each year of 1993-1998. Hayashi and Prescott (2002), in contrast, argue that the declined bank lending did not have a significant impact on investment, since firms could have financed investment by liquidating their own land or financial assets.12

There exists another approach that investigates a dynamic interrelationship between bank-specific factors and firm-specific factors, using vector autoregression (VAR). Sadahiro (2005) finds that the investment slump during the Lost Decade was Granger-caused by a decrease in firm profit and not by bank loans. He therefore claims that a firm-specific

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2See Miyao (2006, Sec. 8.4) for more detailed literature review on the relationship between bank loans and investment.
factor better accounts for the sluggish private investment than a bank-specific factor.\footnote{Mizobata (2015) fits a panel VAR for investment, hiring, and financial indicators of Japanese firms.}

From a methodological point of view, previous papers share a common issue of temporal aggregation. Key variables in this field (e.g. private non-residential investment, firm-specific bank lending for investment, and firm profit) are sampled quarterly or even less frequently. Previous papers were forced to aggregate high frequency variables, such as stock prices and interest rates, since classical models require all variables to have a single frequency. Temporal aggregation is known to have an adverse impact on statistical inference.\footnote{Silvestrini and Veredas (2008) survey the effects of temporal aggregation on time series models.}

The present paper sheds new light on the literature by exploiting mixed frequency data. Analysis of mixed frequency data, called Mixed Data Sampling (MIDAS) regression, was explored by Ghysels, Santa-Clara, and Valkanov (2004), Ghysels, Santa-Clara, and Valkanov (2006), and Andreou, Ghysels, and Kourtellos (2010).\footnote{See Armesto, Engemann, and Owyang (2010) and Andreou, Ghysels, and Kourtellos (2011) for surveys.} In particular, Ghysels, Santa-Clara, and Valkanov (2004) demonstrate that MIDAS regressions lead to more efficient estimation than the classical approach of aggregating all series to the least frequency sampling.

VAR models for mixed frequency data were independently introduced by McCracken, Owyang, and Sekhposyan (2015), Anderson, Deistler, Felsenstein, Funovits, Koelbl, and Zamani (2016), and Ghysels (2016).\footnote{Foroni, Ghysels, and Marcellino (2013) survey mixed frequency VAR models and related literature.} Ghysels’ (2016) mixed frequency VAR (henceforth MF-VAR) is a user-friendly model that does not require any filtering procedure. A major advantage of MF-VAR relative to single-frequency VAR is that high frequency variables are allowed to have heterogeneous impacts on a low frequency variable within each low frequency time period.\footnote{Ghysels, Hill, and Motegi (2016) elaborate the statistical properties of MF-VAR, with a particular focus on Granger causality.}

Not many applied papers use MF-VAR so far, since it is a relatively new tool. We are not aware of any applied paper that analyzes the Japanese economy based on MF-VAR. This paper fills that gap by analyzing the interaction of monthly stock prices, quarterly bank loans, firm profit, and private investment. Stock prices have a close connection with Tobin’s $Q$, one of the most well-known factors associated with private investment.\footnote{See Hayashi (1982), Fazzari, Hubbard, and Petersen (1988), and Abel and Eberly (1994) for early contributions to Tobin’s $Q$-theory. Fore more recent work, see Mizobata (2014) and references therein.} Computation of Tobin’s $Q$ requires corporate net worth data, which are sampled at a quarterly or less frequently level. Stock prices, in contrast, are sampled at much higher frequency than a quarterly level (e.g. monthly, daily, or even intradaily). We compare
a model with quarterly stock prices and a model with monthly stock prices in order to highlight that changing the sampling frequency can alter empirical results considerably.

Our empirical findings are summarized as follows. First, monthly stock prices explain as much as 50.7% of the forecast error variance of private investment in a long-run (i.e. \( h = 12 \) quarters).

Second, based on impulse response analysis, we reveal a spiral of declining stock prices, firm profit, and investment. Lower stock prices affected firm profit negatively, which discouraged firms’ investment. The investment slowdown put a further downward pressure on the stock prices, creating a loop of negative feedback effects.

Third, the stagnation of bank lending is a consequence of a decrease in stock prices, and it is not a cause of a decrease in investment. The long-run forecast error variance of bank lending is explained 41.0% by stock prices. Bank lending, by contrast, has only negligible impacts on stock prices, profit, and investment. Thus, the firm-specific factor (i.e. firm profit) better explains the sluggish investment than the bank-specific factor (i.e. bank lending).

We would need to use quarterly stock prices if we were forced to work with single-frequency data. Aggregating monthly stock prices into a quarterly level underestimates the influence of stock prices. Quarterly stock prices explain 31.8% of the long-run forecast error variance of investment (as opposed to 50.7% in the mixed frequency case). Also, aggregating stock prices weakens the statistical significance of the spiral of stock prices, firm profit, and investment. The impulse response of stock prices to investment is not significant at the 5% level when aggregating the stock prices. The mixed frequency approach therefore yields richer economic insights than the classical approach.

The remainder of the paper is organized as follows. In Section 2 we describe the MF-VAR methodology. In Section 3 we explain our data and perform some preliminary analysis. In Section 4 we present main empirical results. Section 5 concludes the paper.

## 2 Methodology

We begin with a single-frequency VAR and then proceed to a mixed frequency VAR in order to show that the choice of sampling frequency can change empirical results considerably.

### 2.1 Quarterly VAR

Let \( t \in \{1, \ldots, n\} \) signify each quarter. Let \( SP_t^Q \) be a stock price index. Superscript ”Q” is put in order to distinguish a quarterly level from a monthly level explicitly. Let \( BL_t \) be
bank lending to private firms; let $\pi_t$ be firm profit; let $I_t$ be private investment. Assume that each series is sufficiently differenced so that the covariance stationarity is satisfied. See Section 3.2 for detailed discussions of data handling.

As a benchmark, formulate a quarterly VAR(4) model:

$$
\begin{bmatrix}
SP^Q_t \\
BL_t \\
\pi_t \\
I_t
\end{bmatrix}
= \sum_{k=1}^{4}
\begin{bmatrix}
a_{11,k} & a_{12,k} & a_{13,k} & a_{14,k} \\
a_{21,k} & a_{22,k} & a_{23,k} & a_{24,k} \\
a_{31,k} & a_{32,k} & a_{33,k} & a_{34,k} \\
a_{41,k} & a_{42,k} & a_{43,k} & a_{44,k}
\end{bmatrix}
\begin{bmatrix}
SP^Q_{t-k} \\
BL_{t-k} \\
\pi_{t-k} \\
I_{t-k}
\end{bmatrix}
+ \begin{bmatrix}
\epsilon_{1t} \\
\epsilon_{2t} \\
\epsilon_{3t} \\
\epsilon_{4t}
\end{bmatrix}.
$$

(1)

Lag length is set to be 4 quarters so that we can capture potential seasonality. A constant term is omitted to save the number of parameters. We demean each series before fitting the model.

### 2.2 Mixed Frequency VAR

We now formulate Ghysels’ (2016) MF-VAR consisting of monthly stock prices and quarterly $BL$, $\pi$, and $I$. While one could be tempted to choose a weekly or daily level instead of the monthly level, MF-VAR is primarily designed for a small ratio of sampling frequencies.\(^9\)

To express monthly stock prices, let $SP_{jt}$ denote a stock price at the $j$-th month of quarter $t$, where $j \in \{1, 2, 3\}$. For example, if $t$ signifies the first quarter of 2000, then $SP_{1t}$ corresponds to January 2000; $SP_{2t}$ to February 2000; $SP_{3t}$ to March 2000; $SP_{1t+1}$ to April 2000, etc. The quarterly stock price $SP^Q_t$ is interpreted as

$$
SP^Q_t = \frac{1}{3} \sum_{j=1}^{3} SP_{jt}.
$$

(2)

To avoid notational confusion, we distinguish monthly stock prices $\{SP_1, SP_2, SP_3\}$, quarterly stock prices $SP^Q$, and a general notion of stock prices $SP$ hereafter.

\(^9\)Addressing a large ratio of sampling frequencies is an ongoing issue that involves dimension-reduction techniques. See Götze, Hecq, and Smeekes (2016) and Ghysels, Hill, and Motegi (2017) for early contributions.
The MF-VAR(4) model is specified as

\[
\begin{bmatrix}
SP_{1,t} \\
SP_{2,t} \\
SP_{3,t} \\
BL_t \\
I_t
\end{bmatrix} = \sum_{k=1}^{4} \begin{bmatrix}
a_{11,k} & a_{12,k} & a_{13,k} & a_{14,k} & a_{15,k} & a_{16,k} \\
a_{21,k} & a_{22,k} & a_{23,k} & a_{24,k} & a_{25,k} & a_{26,k} \\
a_{31,k} & a_{32,k} & a_{33,k} & a_{34,k} & a_{35,k} & a_{36,k} \\
a_{41,k} & a_{42,k} & a_{43,k} & a_{44,k} & a_{45,k} & a_{46,k} \\
a_{51,k} & a_{52,k} & a_{53,k} & a_{54,k} & a_{55,k} & a_{56,k} \\
a_{61,k} & a_{62,k} & a_{63,k} & a_{64,k} & a_{65,k} & a_{66,k}
\end{bmatrix} \begin{bmatrix}
SP_{1,t-k} \\
SP_{2,t-k} \\
SP_{3,t-k} \\
BL_{t-k} \\
I_{t-k}
\end{bmatrix} + \begin{bmatrix}
\epsilon_{1t} \\
\epsilon_{2t} \\
\epsilon_{3t} \\
\epsilon_{4t} \\
\epsilon_{5t} \\
\epsilon_{6t}
\end{bmatrix},
\]

(3)

or compactly

\[
X_t = \sum_{k=1}^{4} A_k X_{t-k} + \epsilon_t.
\]

(4)

Lag length is set to be 4 quarters for a fair comparison with the quarterly model (1).\(^{10}\)

A key feature of (3) is that \(SP_{1t}, SP_{2t},\) and \(SP_{3t}\) are stacked in a vector. To see an advantage of this approach, pick the last row of (3):

\[
I_t = \sum_{k=1}^{4} \sum_{j=1}^{3} a_{6j,k} SP_{j,t-k} + a_{64,k} BL_{t-k} + a_{65,k} \pi_{t-k} + a_{66,k} I_{t-k} + \epsilon_{6t}.
\]

Since \(a_{61,k}, a_{62,k},\) and \(a_{63,k}\) can take different values from each other, \(SP_{1,t-k}, SP_{2,t-k},\) and \(SP_{3,t-k}\) are allowed to have heterogeneous impacts on \(I_t\). Recall from (1) and (2) that the quarterly model implies that

\[
I_t = \sum_{k=1}^{4} \left( a_{41,k} \left( \frac{1}{3} \sum_{j=1}^{3} SP_{j,t-k} \right) + a_{42,k} BL_{t-k} + a_{43,k} \pi_{t-k} + a_{44,k} I_{t-k} \right) + \epsilon_{4t}.
\]

(5)

Equation (5) assumes implicitly that \(SP_{1,t-k}, SP_{2,t-k},\) and \(SP_{3,t-k}\) have a homogeneous impact of \(a_{41,k}/3\) on \(I_t\). That feature rules out the possibility of seasonal effects and lagged information transmission within each quarter. MF-VAR is more flexible than the quarterly VAR in that regard.

In terms of asymptotic theory, MF-VAR can be treated in the same way as classical VAR—note that MF-VAR model (4) has an identical appearance with a standard VAR with six variables. Standard regularity conditions therefore all carry over. First, we assume that all roots of the polynomial \(\text{det}(I_6 - \sum_{k=1}^{4} A_k z^k) = 0\) lie outside the unit circle, where \(\text{det}(\cdot)\) means the determinant. Second, \(\{\epsilon_t\}\) is a strictly stationary martingale.

\(^{10}\)Model (4) is a reduced-form model. We are not aware of any applied paper with a structural form of Ghysels’ (2016) MF-VAR, and that seems to be an interesting future task. In this paper we focus on reduced form to see how empirical results change by switching from single-frequency VAR to MF-VAR.
difference sequence with finite second moment. Third, $\{X_t, \epsilon_t\}$ obey $\alpha$-mixing. These assumptions ensure the consistency and asymptotic normality of least squares estimator $\hat{A}_k$.\(^{11}\)

We perform impulse response analysis and forecast error variance decomposition for each model. They require a choice of the Cholesky order. We set $SP^Q \to BL \to \pi \to I$ for the quarterly model; $SP_1 \to SP_2 \to SP_3 \to BL \to \pi \to I$ for the mixed frequency model. These orders are in line with actual announcement schedules in Japan. See Section 3.1 for more details.

3 Data and Preliminary Statistics

In this section we explain how our data are retrieved and transformed, and perform some preliminary analysis.

3.1 Data Source

For stock prices, we retrieve a monthly average of daily closing prices of Nikkei Stock Average from Federal Reserve Economic Data. For firm profit, we use "Ordinary Profits, All Industries" within "Financial Statements Statistics of Corporations by Industry" published quarterly by the Ministry of Finance, Japan.

Private non-residential investment, our main objective, is proxied by "Nominal Private Non-Residential Investment" of the System of National Accounts (93SNA), published quarterly by the Economic and Social Research Institute, Cabinet Office. We use figures from annual revisions (as opposed to preliminary estimates).

Bank loan data are less straightforward to organize. Our primary source is "Loans and Bills Discounted by Sector (by Type of Major Industries)" published quarterly by the Bank of Japan. Since we are interested in loans for investment, we focus on a component called "Loans for Fixed Investment". It consists of "Banking Accounts/Domestically Licensed Banks" and "Trusts Accounts/Domestically Licensed Banks". For each account we subtract loans to "Local Governments" and "Households" from loans to "Total Including Others", since we are interested in private non-residential investment. We then sum up the two accounts. The resulting series, which we will analyze hereafter, represents firm-specific bank loans for private investment.\(^{12}\)

\(^{11}\)See Ghysels, Hill, and Motegi (2016) for complete details.
\(^{12}\)The Bank of Japan also publishes "Deposits, Vault Cash, and Loans and Bills Discounted", in which monthly data of firm-specific bank loans for private investment are available. That series, however, is not suitable for the analysis of the Lost Decade since it only dates back to April 1999.
As stated in Section 2, we use the Cholesky decomposition with order $SP \rightarrow BL \rightarrow \pi \rightarrow I$ when performing impulse response analysis and variance decomposition. This order is in line with actual publication schedules in Japan. Stock prices $SP$ are observed almost instantaneously. Bank loans $BL$ are observed roughly in two months and fifteen days (e.g., bank loans for the first quarter of 2000, written as 2000Q1, were announced in the middle of May 2000). Firm profit $\pi$ is observed roughly in three months and a few days (e.g., firm profit for 2000Q1 was announced in early June 2000). Investment $I$ comes last since our figures are based on annual revisions, which take at least three quarters. Investment data for 1999Q2-2000Q1 were revised in December 2000; investment data for 2000Q2-2001Q1 were revised in December 2001, etc.

### 3.2 Preliminary Sample Statistics

Our sample period covers 204 months (68 quarters) between January 1990 and December 2006. There is a broad consensus that the Lost Decade was triggered by the stock market bubble burst in early 1990. It is thus reasonable to start our sample period at 1990Q1.

We choose 2006Q4 as the end of our sample period, based on the trend of bank lending. The outstanding of bank loans was growing at about 15% from previous year in early 1990. The growth rate kept slowing down to hit 0% in 1994 and then remained negative for about 12 consecutive years. Bank loans finally began increasing in late 2006, a symbolic phenomenon suggesting the end of the Lost Decade.

Based on Phillips and Perron’s (1988) unit root test with and without a time trend, we decided to take the first difference for $\{SP, \pi, I\}$ and the second difference for $BL$ in order to ensure stationarity. For the former, we compute 100 times year-to-year log difference of the level series. For the latter, we compute changes in 100 times year-to-year log difference of the outstanding of the bank loans. We took the year-to-year difference in order to eliminate potential seasonality.

In Table 1, we report the result of the Phillips-Perron tests for the sufficiently differenced versions of $\{SP_1, SP_2, SP_3, SP^Q, BL, \pi, I\}$. We consider two specifications for the test equation. In the first case, an intercept is included and a trend is not included. In the second case, both intercept and trend are included. Bartlet kernel with the Newey-and-West automatic bandwidth selection is used for each case.

Insert Table 1 here.

When the test equation has an intercept only, the null hypothesis of unit root is rejected at the 10% level for investment and 5% level for all other series. When the test
equation has both intercept and trend, the null hypothesis is not rejected at the 10% level for investment with p-value 0.215; it is rejected at the 10% level for $SP^Q_t$ and $\pi_t$; it is rejected at the 5% level for all other series. The results for investment are mixed, but we assume that stationarity is satisfied in view of the test result without a trend.

In Figure 1 we present time series plots of the sufficiently differenced series. From a visual inspection, we observe a positive correlation between stock prices and firm profit. These series seem to be followed by private investment. We thus expect that stock prices and profit should be relevant factors that predict investment. It is not clear from Figure 1 how bank loans are affecting or affected by other series.

Insert Figure 1 here.

Table 2 reports sample statistics of the differenced series. $SP_1$, $SP_2$, and $SP_3$ have some interesting differences. First, their median is -6.173%, -7.231%, and -5.030% respectively. $SP_2$ has worse performance by 2.201% points than $SP_3$. Second, $SP_3$ has weaker asymmetry than $SP_1$ and $SP_2$ in terms of skewness. The heterogeneous characteristics of $SP_1$, $SP_2$, and $SP_3$ suggest a potential benefit of the MF-VAR.

Insert Table 2 here.

The Kolmogorov-Smirnov test rejects the null hypothesis of normality for bank loans at the 10% level. The Anderson-Darling test rejects the null hypothesis of normality for bank loans at 1%, investment at 5%, and profit at 10%. Hence these series (especially bank loans) likely have non-normal distributions. As demonstrated in Ghysels, Hill, and Motegi (2016), the asymptotic theory of (MF-)VAR models does not require the normality assumption.

Contemporaneous and lagged correlation coefficients between each pair of variables confirm the visual lead/lag relationships observed in Figure 1. First, the correlation between $SP^Q_t$ and $\pi_t$ is fairly large at 0.580. We get similar results after replacing $SP^Q_t$ with $SP_{1t}$, $SP_{2t}$, or $SP_{3t}$. Second, the correlations between $I_t$ and $SP^Q_{t-k}$ are peaked at the fourth lag with 0.311, 0.437, 0.530, 0.589, and 0.522 for $k = 1, \ldots, 5$. Replacing $SP^Q_{t-k}$ with $SP_{1,t-k}$, $SP_{2,t-k}$, or $SP_{3,t-k}$ yields similar results. Third, the correlations between $I_t$ and $\pi_{t-k}$ are peaked at the second lag with 0.650, 0.761, and 0.723 for $k = 1, 2, 3$.

\footnote{Tables or figures of correlations are omitted for brevity but available upon request.}
4 Empirical Results

This section reports our empirical results for the quarterly and mixed frequency VAR models.

4.1 Quarterly VAR

We first discuss the quarterly VAR model. See Figure 2 for impulse response functions (IRFs) with 95% confidence intervals. The confidence intervals are constructed by parametric bootstrap for each horizon \( h = 0, 1, \ldots, 10 \), using the least squares estimator \( \hat{A}_k \), error covariance estimator \( \hat{\Omega} = (1/n) \sum_{t=1}^{n} \hat{\epsilon}_t \hat{\epsilon}_t' \), and normal random numbers. The number of bootstrap samples is 10,000.

Insert Figure 2 here.

First, the IRF of private investment \( I \) to a 1σ shock in stock prices \( SP^Q \), written as “\( SP^Q \rightarrow I \)”, is significantly positive at horizons \( h = 4, 5, 6, 7 \). This result is consistent with the fact that the correlation coefficient between \( I_t \) and \( SP^Q_{t-k} \) reaches a peak of 0.589 when \( k = 4 \). Second, \( \pi \rightarrow I \) is significantly positive at \( h = 0, 2, 3 \). This result is again consistent with the fact that the correlation between \( I_t \) and \( \pi_{t-k} \) reaches a peak of 0.761 when \( k = 2 \). Third, \( BL \rightarrow I \) is clearly insignificant at any horizon, a strong evidence against the bank-specific factor. Hence, stock prices and firm profit are likely primary drivers of private investment.

In Table 3, the forecast error variance decomposition of investment confirms the large explanatory power of stock prices and profit and the small explanatory power of bank loans. In the long-run \( h = 12 \), the forecast error variance of \( I \) is explained 31.8% by \( SP^Q \), 6.3% by \( BL \), 25.5% by \( \pi \), and 36.4% by \( I \) itself.

Insert Table 3 here.

The quarterly VAR exhibits a relatively weak degree of interdependence. Table 3 indicates that 82.7% of the long-run forecast error variance of \( SP^Q \), 70.7% of \( BL \), 45.6% of \( \pi \), and 36.4% of \( I \) are explained by themselves. In particular, it is somewhat unsatisfactory that the model explains only 100 – 36.4 = 63.6% of our main target \( I \). Also, the IRFs of \( SP^Q \) to \( BL \), \( \pi \), and \( I \) are all insignificant at any horizon (Panels 1-3 of Figure 2).
4.2 Mixed Frequency VAR

We now discuss the MF-VAR model. See Figure 3.A-3.C for IRFs. Figure 3.A shows IRFs of \( SP \) to other variables; Figure 3.B shows IRFs of \( \{BL, \pi, I\} \) to \( SP \); Figure 3.C shows IRFs not involving \( SP \).


We first focus on how our main target \( I \) is explained in MF-VAR. In Figure 3.C, \( \pi \rightarrow I \) is significantly positive at \( h = 0, 1, 2, 3 \), again suggesting the relevance of the firm-specific factor. Also, \( SP_1 \rightarrow I \) is significantly positive at \( h = 5, 6, 7 \); \( SP_3 \rightarrow I \) is significantly positive at \( h = 2 \) (Figure 3.B). Finally, \( BL \rightarrow I \) is far from significant at any horizon, a strong evidence against the bank-specific factor (Figure 3.C). These results are consistent with the quarterly model, and also with Sadahiro (2005), who finds that the firm-specific factor outweighs the bank-specific factor.

The MF-VAR achieves greater explanatory power on investment than the quarterly VAR. In Table 4, the long-run forecast error variance of \( I \) is attributed to \( SP_1 \) by 22.6%, \( SP_2 \) by 18.2%, \( SP_3 \) by 9.9%, \( BL \) by 2.0%, \( \pi \) by 22.4%, and \( I \) itself by 24.9%. The total contribution of stock prices is as large as 22.6 + 18.2 + 9.9 = 50.7% as opposed to 31.8% in the quarterly VAR. It suggests that aggregating monthly stock prices into a quarterly level underestimates the influence of stock prices.

Insert Table 4 here.

We next discuss an overall interaction in the entire model. In view of Table 4, the MF-VAR accounts for 52.3% of the long-run forecast error variance of \( BL \), 70.2% of \( \pi \), and 75.1% of \( I \), net of their own contributions. Recall from Table 3 that the portion was 29.3% for \( BL \), 54.4% for \( \pi \), and 63.6% for \( I \) in the quarterly VAR. Hence the mixed frequency approach delivers a tighter interdependence than the quarterly approach.

Impulse responses in the MF-VAR also provide richer implications than in the quarterly VAR. Recall from Figure 2 that five pairs have significant IRFs in the quarterly VAR: \( SP^Q \rightarrow BL \), \( SP^Q \rightarrow \pi \), \( BL \rightarrow \pi \), \( SP^Q \rightarrow I \), and \( \pi \rightarrow I \). In view of Figures 3.A-3.C, the MF-VAR preserves all those patterns except for \( BL \rightarrow \pi \), which was only marginally significant in the quarterly VAR. (\( SP^Q \) is now replaced with \( SP_1 \), \( SP_2 \), or \( SP_3 \).)

Besides those pairs, the MF-VAR produces three more cases of significant IRFs: \( I \rightarrow SP_1 \) at \( h = 1, 3 \); \( I \rightarrow SP_2 \) at \( h = 3 \); \( I \rightarrow SP_3 \) at \( h = 2 \). These extra results imply that each of \( SP \), \( BL \), \( \pi \), and \( I \) is significantly explained by at least one variable.
To summarize the impulse response analysis, the MF-VAR provides an interesting picture on how investment and other variables interact to each other. There is a spiral that \( SP \rightarrow \pi \rightarrow I \rightarrow SP \). A decrease in stock prices lowered the firm profit, which discouraged firms from investing. The declined investment put a further downward pressure on the stock prices, creating a loop of negative feedback effects. Note that the spiral \( SP \rightarrow \pi \rightarrow I \rightarrow SP \) is less apparent in the quarterly VAR, since the IRF of \( SP^Q \) to \( I \) is not significant at the 5% level (Panel 3, Figure 2). The mixed frequency approach therefore yields richer economic insights than the single-frequency approach.

Finally, both approaches indicate that a decrease in bank loans is a consequence of a decrease in stock prices, and it is not a cause of the declined investment. We thus conclude that the firm-specific factor outweighs the bank-specific factor in terms of explaining the investment stagnation.

5 Conclusions

This paper reconsiders the sluggish private investment in Japan’s Lost Decade, using a recent tool of MF-VAR. Our model consists of monthly stock prices \( SP \), quarterly bank loans \( BL \), firm profit \( \pi \), and investment \( I \). The classical VAR aggregates the monthly stock prices into a quarterly level. An advantage of MF-VAR is that monthly stock prices are allowed to have heterogeneous impacts on the other quarterly series.

Our empirical results are summarized as follows. First, monthly stock prices account for as much as 50.7% of the long-run forecast error variance of private investment. Second, we have revealed a spiral that \( SP \rightarrow \pi \rightarrow I \rightarrow SP \). Third, a decrease in bank loans is a consequence of a decrease in stock prices, and it is not a cause of the declined investment. We therefore conclude that the firm-specific factor (i.e. firm profit) better explains the sluggish investment than the bank-specific factor (i.e. bank lending).

Aggregating monthly stock prices into a quarterly level underestimates the influence of stock prices. Quarterly stock prices explain 31.8% of the long-run forecast error variance of investment (as opposed to 50.7% in the MF-VAR). Also, the temporal aggregation of stock prices makes the spiral \( SP \rightarrow \pi \rightarrow I \rightarrow SP \) less apparent due to the insignificant impulse response of \( SP \) to \( I \). Overall, the mixed frequency approach yields richer economic insights than the single-frequency approach.

References


Table 1: P-Values of Phillips-Perron Unit Root Tests

<table>
<thead>
<tr>
<th></th>
<th>$SP_1$</th>
<th>$SP_2$</th>
<th>$SP_3$</th>
<th>$SP^{Q}$</th>
<th>$BL$</th>
<th>$\pi$</th>
<th>$I$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept Only</td>
<td>0.012</td>
<td>0.019</td>
<td>0.012</td>
<td>0.026</td>
<td>0.000</td>
<td>0.024</td>
<td>0.062</td>
</tr>
<tr>
<td>Intercept &amp; Trend</td>
<td>0.021</td>
<td>0.031</td>
<td>0.025</td>
<td>0.062</td>
<td>0.000</td>
<td>0.058</td>
<td>0.215</td>
</tr>
</tbody>
</table>

We perform Phillips and Perron’s (1988) unit root test. We consider two specifications for the test equation. In the first case, an intercept is included and a trend is not included. In the second case, both intercept and trend are included. Bartlet kernel with the Newey-and-West automatic bandwidth selection is used for each case. The null hypothesis is that there exists a unit root. For stock prices, firm profit, and private investment, the test variable is 100 times year-to-year log difference of the level series. For bank lending, the test variable is changes in 100 times year-to-year log difference of the outstanding of the bank lending.
Table 2: Sample Statistics of Differenced Series

<table>
<thead>
<tr>
<th></th>
<th>$SP_1$</th>
<th>$SP_2$</th>
<th>$SP_3$</th>
<th>$SP^Q$</th>
<th>$BL$</th>
<th>$\pi$</th>
<th>$I$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>-4.237</td>
<td>-4.429</td>
<td>-4.514</td>
<td>-4.393</td>
<td>-0.193</td>
<td>2.327</td>
<td>-0.402</td>
</tr>
<tr>
<td>Median</td>
<td>-6.173</td>
<td>-7.231</td>
<td>-5.030</td>
<td>-7.379</td>
<td>-0.360</td>
<td>7.096</td>
<td>1.254</td>
</tr>
<tr>
<td>Minimum</td>
<td>-47.24</td>
<td>-42.90</td>
<td>-48.08</td>
<td>-43.22</td>
<td>-4.524</td>
<td>-50.12</td>
<td>-17.47</td>
</tr>
<tr>
<td>Maximum</td>
<td>41.36</td>
<td>38.72</td>
<td>38.88</td>
<td>35.81</td>
<td>6.390</td>
<td>34.93</td>
<td>14.67</td>
</tr>
<tr>
<td>Std. Dev.</td>
<td>22.49</td>
<td>21.34</td>
<td>21.52</td>
<td>21.06</td>
<td>1.517</td>
<td>20.43</td>
<td>7.467</td>
</tr>
<tr>
<td>Skewness</td>
<td>0.105</td>
<td>0.114</td>
<td>0.005</td>
<td>0.135</td>
<td>1.281</td>
<td>-0.536</td>
<td>-0.384</td>
</tr>
<tr>
<td>Kurtosis</td>
<td>2.108</td>
<td>2.001</td>
<td>2.240</td>
<td>2.003</td>
<td>9.572</td>
<td>2.627</td>
<td>2.726</td>
</tr>
<tr>
<td>p-KS</td>
<td>0.782</td>
<td>0.513</td>
<td>0.942</td>
<td>0.708</td>
<td>0.058</td>
<td>0.384</td>
<td>0.318</td>
</tr>
<tr>
<td>p-AD</td>
<td>0.343</td>
<td>0.126</td>
<td>0.804</td>
<td>0.114</td>
<td>0.000</td>
<td>0.052</td>
<td>0.041</td>
</tr>
</tbody>
</table>

{$SP_1, SP_2, SP_3$} signify monthly stock prices; $SP^Q$ signifies quarterly stock prices; $BL$ signifies bank loans; $\pi$ signifies firm profit; $I$ signifies private investment. For $BL$, we take changes in 100 times year-to-year log difference of the outstanding of bank lending. For all other series we take 100 times year-to-year log difference of the level series. Sample period covers 204 months (68 quarters) from 1990Q1 through 2006Q4. 'p-KS' signifies a p-value of the Kolmogorov-Smirnov test for normality. 'p-AD' signifies a p-value of the Anderson-Darling test for normality.
Table 3: Forecast Error Variance Decomposition of Quarterly VAR(4)

<table>
<thead>
<tr>
<th>Decomposition of $SP^Q$</th>
<th>Decomposition of $BL$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$SP^Q$</td>
<td>$BL$</td>
</tr>
<tr>
<td>$h = 4$</td>
<td>.858</td>
</tr>
<tr>
<td>$h = 8$</td>
<td>.838</td>
</tr>
<tr>
<td>$h = 12$</td>
<td>.827</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Decomposition of $\pi$</th>
<th>Decomposition of $I$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$SP^Q$</td>
<td>$BL$</td>
</tr>
<tr>
<td>$h = 4$</td>
<td>.332</td>
</tr>
<tr>
<td>$h = 8$</td>
<td>.321</td>
</tr>
<tr>
<td>$h = 12$</td>
<td>.367</td>
</tr>
</tbody>
</table>

The model is VAR(4) of quarterly stock prices $SP^Q$, bank loans $BL$, firm profit $\pi$, and private investment $I$. In this table we perform the forecast error variance decomposition of each series at prediction horizons $h = 4, 8, 12$ quarters. Sample period covers 1990Q1-2006Q4 (68 quarters).
Table 4: Forecast Error Variance Decomposition of MF-VAR(4)

<table>
<thead>
<tr>
<th>Decomposition of $SP_1$</th>
<th>$SP_1$</th>
<th>$SP_2$</th>
<th>$SP_3$</th>
<th>$(\sum_{j=1}^3 SP_j)$</th>
<th>$BL$</th>
<th>$\pi$</th>
<th>$I$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$h = 4$</td>
<td>.321</td>
<td>.348</td>
<td>.163</td>
<td>(.832)</td>
<td>.024</td>
<td>.002</td>
<td>.143</td>
</tr>
<tr>
<td>$h = 8$</td>
<td>.301</td>
<td>.323</td>
<td>.193</td>
<td>(.817)</td>
<td>.030</td>
<td>.006</td>
<td>.147</td>
</tr>
<tr>
<td>$h = 12$</td>
<td>.296</td>
<td>.319</td>
<td>.203</td>
<td>(.818)</td>
<td>.031</td>
<td>.007</td>
<td>.146</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Decomposition of $SP_2$</th>
<th>$SP_1$</th>
<th>$SP_2$</th>
<th>$SP_3$</th>
<th>$(\sum_{j=1}^3 SP_j)$</th>
<th>$BL$</th>
<th>$\pi$</th>
<th>$I$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$h = 4$</td>
<td>.345</td>
<td>.353</td>
<td>.153</td>
<td>(.851)</td>
<td>.016</td>
<td>.004</td>
<td>.128</td>
</tr>
<tr>
<td>$h = 8$</td>
<td>.325</td>
<td>.330</td>
<td>.183</td>
<td>(.838)</td>
<td>.025</td>
<td>.010</td>
<td>.127</td>
</tr>
<tr>
<td>$h = 12$</td>
<td>.320</td>
<td>.326</td>
<td>.191</td>
<td>(.837)</td>
<td>.026</td>
<td>.011</td>
<td>.126</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Decomposition of $SP_3$</th>
<th>$SP_1$</th>
<th>$SP_2$</th>
<th>$SP_3$</th>
<th>$(\sum_{j=1}^3 SP_j)$</th>
<th>$BL$</th>
<th>$\pi$</th>
<th>$I$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$h = 4$</td>
<td>.316</td>
<td>.353</td>
<td>.185</td>
<td>(.854)</td>
<td>.016</td>
<td>.003</td>
<td>.129</td>
</tr>
<tr>
<td>$h = 8$</td>
<td>.302</td>
<td>.336</td>
<td>.206</td>
<td>(.844)</td>
<td>.018</td>
<td>.008</td>
<td>.130</td>
</tr>
<tr>
<td>$h = 12$</td>
<td>.298</td>
<td>.332</td>
<td>.213</td>
<td>(.843)</td>
<td>.019</td>
<td>.009</td>
<td>.128</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Decomposition of $BL$</th>
<th>$SP_1$</th>
<th>$SP_2$</th>
<th>$SP_3$</th>
<th>$(\sum_{j=1}^3 SP_j)$</th>
<th>$BL$</th>
<th>$\pi$</th>
<th>$I$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$h = 4$</td>
<td>.038</td>
<td>.124</td>
<td>.212</td>
<td>(.374)</td>
<td>.543</td>
<td>.038</td>
<td>.045</td>
</tr>
<tr>
<td>$h = 8$</td>
<td>.058</td>
<td>.132</td>
<td>.208</td>
<td>(.398)</td>
<td>.497</td>
<td>.060</td>
<td>.046</td>
</tr>
<tr>
<td>$h = 12$</td>
<td>.072</td>
<td>.134</td>
<td>.204</td>
<td>(.410)</td>
<td>.477</td>
<td>.067</td>
<td>.046</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Decomposition of $\pi$</th>
<th>$SP_1$</th>
<th>$SP_2$</th>
<th>$SP_3$</th>
<th>$(\sum_{j=1}^3 SP_j)$</th>
<th>$BL$</th>
<th>$\pi$</th>
<th>$I$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$h = 4$</td>
<td>.245</td>
<td>.036</td>
<td>.220</td>
<td>(.501)</td>
<td>.035</td>
<td>.389</td>
<td>.076</td>
</tr>
<tr>
<td>$h = 8$</td>
<td>.295</td>
<td>.048</td>
<td>.214</td>
<td>(.557)</td>
<td>.032</td>
<td>.337</td>
<td>.074</td>
</tr>
<tr>
<td>$h = 12$</td>
<td>.284</td>
<td>.102</td>
<td>.194</td>
<td>(.580)</td>
<td>.029</td>
<td>.298</td>
<td>.094</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Decomposition of $I$</th>
<th>$SP_1$</th>
<th>$SP_2$</th>
<th>$SP_3$</th>
<th>$(\sum_{j=1}^3 SP_j)$</th>
<th>$BL$</th>
<th>$\pi$</th>
<th>$I$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$h = 4$</td>
<td>.064</td>
<td>.066</td>
<td>.149</td>
<td>(.279)</td>
<td>.020</td>
<td>.346</td>
<td>.355</td>
</tr>
<tr>
<td>$h = 8$</td>
<td>.223</td>
<td>.175</td>
<td>.100</td>
<td>(.498)</td>
<td>.019</td>
<td>.223</td>
<td>.259</td>
</tr>
<tr>
<td>$h = 12$</td>
<td>.226</td>
<td>.182</td>
<td>.099</td>
<td>(.507)</td>
<td>.020</td>
<td>.224</td>
<td>.249</td>
</tr>
</tbody>
</table>

The model is MF-VAR(4) of monthly stock prices \{SP_1, SP_2, SP_3\}, quarterly bank loans $BL$, firm profit $\pi$, and private investment $I$. In this table we perform the forecast error variance decomposition of each series at prediction horizons $h = 4, 8, 12$ quarters. Sample period covers 1990Q1-2006Q4 (204 months, 68 quarters).
Figure 1: Stock Prices, Bank Loans, Firm Profit, and Private Investment

(a) Monthly Stock Prices

(b) Quarterly Bank Loans

(c) Quarterly Firm Profit

(d) Quarterly Private Investment

For (a) monthly stock prices, (c) quarterly firm profit, and (d) quarterly private investment, we plot 100 times year-to-year log difference of the level series. For (b) quarterly bank loans, we plot changes in 100 times year-to-year log difference of the outstanding of bank loans. Sample period covers 204 months (68 quarters) from January 1990 through December 2006. For the monthly series, "Jan90" signifies January 1990. For the quarterly series, "Q1-90" signifies the first quarter of 1990. Note that y-range differs across panels for visual clarity.
This figure plots impulse response functions based on the quarterly VAR(4) of stock prices $SP^Q$, bank loans $BL$, firm profit $\pi$, and private investment $I$. We use the Cholesky decomposition with order $SP^Q \rightarrow BL \rightarrow \pi \rightarrow I$. Sample period covers 1990Q1-2006Q4. Panel 1, for example, plots the impulse response of $SP^Q$ to a 1σ shock in $BL$, written as "$BL \rightarrow SP^Q$", for quarterly horizons $h = 0, 1, \ldots, 10$. For each horizon 95% confidence intervals are constructed by parametric bootstrap with 10,000 replications.
Figures 3.A-3.C plot impulse response functions (IRFs) for quarterly horizons $h = 0, 1, \ldots, 10$ based on the MF-VAR(4) of monthly stock prices $\{SP_1, SP_2, SP_3\}$, quarterly bank loans $BL$, firm profit $\pi$, and private investment $I$. We use the Cholesky decomposition with order $SP_1 \to SP_2 \to SP_3 \to BL \to \pi \to I$. Sample period covers 1990Q1-2006Q4. For each horizon $h$, 95% confidence intervals are constructed by parametric bootstrap with 10,000 replications. Figure 3.A shows IRFs of stock prices to other variables. Panel A.1, for example, plots the IRF of $SP_1$ to a $1\sigma$ shock in $BL$, written as "$BL \to SP_1$".
Figures 3.A-3.C plot impulse response functions (IRFs) for quarterly horizons $h = 0,1,...,10$ based on the MF-VAR(4) of monthly stock prices $\{SP_1, SP_2, SP_3\}$, quarterly bank loans $BL$, firm profit $\pi$, and private investment $I$. We use the Cholesky decomposition with order $SP_1 \rightarrow SP_2 \rightarrow SP_3 \rightarrow BL \rightarrow \pi \rightarrow I$. Sample period covers 1990Q1-2006Q4. For each horizon $h$, 95% confidence intervals are constructed by parametric bootstrap with 10,000 replications. Figure 3.B shows IRFs of $BL$, $\pi$, and $I$ to stock prices. Panel B.1, for example, plots the IRF of $BL$ to a $1\sigma$ shock in $SP_1$, written as "$SP_1 \rightarrow BL$".
Figures 3.A-3.C plot impulse response functions (IRFs) for quarterly horizons $h = 0, 1, \ldots, 10$ based on the MF-VAR(4) of monthly stock prices $\{SP_1, SP_2, SP_3\}$, quarterly bank loans $BL$, firm profit $\pi$, and private investment $I$. We use the Cholesky decomposition with order $SP_1 \rightarrow SP_2 \rightarrow SP_3 \rightarrow BL \rightarrow \pi \rightarrow I$. Sample period covers 1990Q1-2006Q4. For each horizon $h$, 95% confidence intervals are constructed by parametric bootstrap with 10,000 replications. Figure 3.C shows IRFs not involving stock prices. Panel C.1, for example, plots the IRF of $BL$ to a 1σ shock in $\pi$, written as "$\pi \rightarrow BL"."