Output Effects of Infrastructure Investment in the Netherlands, 1853–1913*

Using a new data set that allows for a distinction between transport and other categories of infrastructure investment, this paper finds strong evidence of a positive impact of transport infrastructure investment on Dutch GDP in the second half of the nineteenth century. However, as the time-series characteristics do not allow us to find permanent effects, these are short- and medium-run effects. We employ Granger-causality tests in a Vector AutoRegression (VAR) framework. Furthermore, the VAR models are analyzed using innovation accounting.

1. Introduction
Recent years have witnessed a remarkable swell of interest in public infrastructure spending as a strategy to promote economic development. While specialists in regional, local and historical economic development have long recognized higher infrastructure investment as a means to enhance growth,1 the genesis of this renewed attention is David Aschauer’s (1989) research on the impact of government investment on private sector productivity. Aschauer hypothesized that the decrease in productive government services might be an explanation for the productivity slowdown in the United States in the 1970s. He tested this hypothesis by running regressions derived from a standard Cobb-Douglas production function augmented by public capital. Unlike several previous studies, Aschauer’s results lead to the conclusion that public capital is productive, and not just a possible inducement to business location.

In this paper we investigate the robustness of the claim that infrastructure investment has positive effects on output. So far, only the post–World War II period has been extensively explored in the literature. We exploit the

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Groote (1996) long-run dataset on infrastructural capital formation in the Netherlands in the nineteenth century. At that time the Netherlands went through the industrial revolution; large infrastructure projects were carried out. For example, the construction of a national railway network started in 1860, and the existing system of natural and artificial waterways was enlarged, integrated, and modernized after 1850. It seems plausible then, that these infrastructural investments induced—or at least enabled—the integration of markets that were regionally and functionally separated before and thereby stimulated economic growth. This paper gives a quantitative underpinning of the belief that investments in transport infrastructures, such as roads, canals and railways, had large positive effects on the production level of the Dutch economy in the previous century.

The methodology of Aschauer (1989) and his followers has been criticized on several grounds (Sturm, Kuper and de Haan 1998). First, the adoption of the production function approach is too restrictive. Interregional, intersectoral and intertemporal allocation and distribution effects, trade effects, agglomeration effects, consequences for the public budget, employment effects as well as direct consumption and welfare effects are ignored. Second, Aschauer and his followers duck the issue of causality. Eisner (1991) for instance questions whether the leveling off of public capital has reduced the growth of output, or whether the reduced growth of output has diminished the demand for public capital. Third, Aschauer does not take the time-series properties of the variables into account (Evans and Karras 1994a, 1994b; Sturm and De Haan 1995; Sturm 1998).

The criticisms led us to use an atheoretic econometric method: we apply Granger-causality tests within the framework of Vector Auto-Regression (VAR) models as propagated by Sims (1980). In a VAR model a limited number of variables is distinguished that are explained by their own lags and lags of the other variables. We use innovation accounting, that is, impulse responses and variance decompositions, to analyze the effect of infrastructure investments over time.

We find strong evidence of a Granger-causal relationship between infrastructure investment and GDP in the Netherlands in the second half of the nineteenth century. We interpret this evidence as a quantitative underpinning of the claim that infrastructure induced economic growth. However, our statistical framework does not allow us to rule out the situation that infrastructure rose in anticipation of future GDP growth.

We have traced only three VAR studies that test the effects of public capital spending on the private sector: Clarida (1993), McMillin and Smyth (1994), and Otto and Voss (1996). We refer to Sturm, Kuper and de Haan (1998) for a thorough discussion of these papers. The main conclusion of
these papers is that there is no clear evidence for the thesis that public capital spending influences output or productivity.\textsuperscript{2}

The paper is structured as follows. Section 2 presents the VAR methodology. Section 3 describes the data and the time-series properties. Section 4 presents our estimation results. The paper concludes with a discussion of our findings.

2. VAR Analysis

To test whether infrastructure influences GDP we first perform Granger-causality analysis and rephrase it as follows: infrastructural capital formation is said to “Granger-cause” a rise in GDP, if the time-series prediction of GDP from its own past improves when lags of infrastructural capital formation are added to the equation. This interpretation of causality is intuitively attractive. It has therefore become widely accepted, although some of its implications are still under debate.\textsuperscript{3} A drawback of the concept is that it cannot discriminate between infrastructure investments causing GDP to rise and infrastructure rising in anticipation of future GDP growth.

Simple Granger-causality analysis may be obstructed by simultaneity effects: infrastructural capital formation may Granger-cause GDP, while GDP also Granger-causes infrastructural capital formation. To avoid this problem, we analyze Granger causality in a Vector AutoRegression (VAR) model.

VAR methodology resembles simultaneous-equation modeling in that several endogenous variables are considered together.

In a VAR each variable is explained by its own lagged values and the lagged values of the other endogenous variables. If necessary, deterministic variables, such as a constant or a trend, are included. The simultaneity problem is solved in a trivial way: no a priori identifying conditions concerning the causal relationship of the variables are needed.

A general VAR model with \( p \) lags, a so-called VAR(\( p \)) model, for a vector \( Y \) of \( k \) endogenous variables has the following form:

\[
Y_t = \sum_{i=1}^{p} A_i Y_{t-i} + D_t + e_t ,
\]

where \( A_i, i = 1, \ldots, p \) are \( k \times k \) matrices of parameters, \( D_t \) is a vector of

\textsuperscript{2}Clarida (1993) finds a long-run equilibrium relationship between multifactor productivity and the stock of public capital. The causality, however, is not clear.

\textsuperscript{3}For an early overview of pros and cons of Granger causality, see Granger (1980).
deterministic variables, like a constant and a trend, and \(e_t\) is a \(k\)-vector of disturbances with mean zero and variance-covariance matrix \(\Sigma\). In case the order \(p\) is known, each equation in the system can be estimated by OLS. Moreover, OLS estimates are consistent and asymptotically efficient (Harvey 1990, 68).

A practical disadvantage of VAR is that the number of parameters to be estimated can easily become large. One additional lag in the VAR model brings in \(k^2\) extra parameters. This quickly chews up degrees of freedom in the estimation procedure. Often, several parameters hardly differ from zero. Imposing common lag lengths, which is often done in empirical research, is not justifiable as it can distort the estimates and may lead to misleading inferences concerning causality, if lag structures differ across variables (Ahking and Miller 1985; Thornton and Batten 1985). To overcome this problem Hsiao (1981) suggests starting from a univariate autoregression and sequentially adding lags and variables using Akaike’s (1969, 1970) Final Prediction Error (FPE) criterion (Canova 1995, 62–63). We use the FPE criterion to select the appropriate lag specification for the individual variables in each equation (VAR-FPE model).\(^4\) The qualitative conclusions do not change when we impose common lag lengths (see Sturm 1998, chap. 7).

Two drawbacks of the FPE-criterion approach should be mentioned. First, the sequential nature of the procedure may bias the joint nature of the process and the single-equation approach is equivalent to ignoring the effect of possible correlation between the residuals. Therefore, we have carried out diagnostic checks to examine the adequacy of our VAR-FPE model specifications. This is done by deliberately underfitting and overfitting the system and testing the system-wide restrictions we impose. The presented results are very robust and all restrictions we impose are accepted by the data. Second, application of the FPE criterion reduces the complexity of the model itself, but increases the complexity of its estimation. As the right-hand-side variables in the equations may now differ, a gain in efficiency can occur by using a system estimator. We apply the Seemingly Unrelated Regression (SUR) estimator of Zellner (1962).

Hsiao (1981) has shown that under fairly general conditions the inclusion of a variable based on the FPE criterion is evidence for a weak Granger-causal relationship. If the lagged values of the explanatory variable further exert a statistically significant effect, then the Granger-causal impact can be identified as a strong form (Kawai 1980).

The Granger-causality testing procedure does in general not give us the sign of the overall effect. To test whether there exists a positive or neg-

ative effect of one variable on another, we apply a neutrality test in which we calculate the sum of the lagged values of an explanatory variable and test whether it significantly differs from zero (Zarnowitz 1992, 365–79). Because the error terms might be correlated across equations, standard F-tests are not applicable; we apply likelihood ratio tests instead.

As links between the equations hamper interpretation of individual coefficients, Sims (1980) proposed to analyze a VAR model by observing the reactions over time of different shocks on the estimated system. Just as an autoregression has a moving average representation, a VAR can be converted into a Vector Moving Average (VMA). The VMA representation allows us to trace the time path of various shocks on the variables in the VAR system.

Because the error terms are contemporaneously correlated, shocks that hit the economy affect all variables in the current period. Consequently, it is not possible to single out the effect of a separate shock. A standard solution for this identification problem is to impose restrictions of some kind. We use the Choleski factorization, which implies an ordering of the variables from the most pervasive—a shock to this variable affects all the other variables in the current period—to the least pervasive—a shock does not affect any other variable in the current period. In this manner some economic structure is imposed on the computation of the impulse-response functions. Unfortunately, there are many ways to order the variables (for $k$ variables there are $k!$ orderings), and, as noted by, for example, Cooley and LeRoy (1985) and Duggal, Saltzman and Klein (1995), the choice of one particular ordering might not be innocuous. Of course, the importance of the ordering depends on the magnitude of the correlation coefficient between the error terms. In case the estimated correlations are almost zero, the ordering is immaterial.

To give an indication of statistical reliability, we report the impulse-responses along with a 95% confidence interval, computed using a procedure developed by Giannini (1992), which is based on asymptotic Gaussian approximations of the distribution of the responses.

Next we apply variance decomposition analysis. The forecast error variance decomposition tells us the proportion of the movements in a sequence due to its “own” shocks versus shocks which may be ascribed to the other variables. If, for example, shocks in infrastructure explain none of the forecast error variance of GDP at all forecast horizons, we can say that GDP is exogenous to infrastructure investment. In that case, GDP evolves independent of the infrastructure shocks and the infrastructure sequence. At the other extreme, infrastructure shocks could explain all the forecast error variance in GDP at all forecast horizons, so that GDP would be entirely endogenous. Generally a variable explains almost all its forecast error variance at short horizons and smaller proportions at longer horizons. In the variance
decomposition analysis we face the same identification problem as in impulse-response analysis. Again we apply the Choleski factorization.

To decompose the standard error of forecast we assume that the coefficients of the model are known, so the standard error of forecast is lower than the true uncertainty with estimated coefficients. We ignore this sampling error term, which depends upon the squares of the coefficients and becomes extremely complicated as the size of the model and the number of forecast steps increases. Instead, we concentrate upon the ones due to the effects of the innovations. Again we use the procedure suggested by Giannini (1992) to calculate standard errors.

3. Data

Description

This paper builds on three new datasets regarding Dutch economic development in the nineteenth century. These are the outcome of research efforts of participants in the project on "The Reconstruction of Dutch National Accounts, and the Analysis of the Development of the Dutch Economy, 1800–1940," which has been under way since 1989 at the universities of Utrecht and Groningen.

Our VAR model includes GDP, infrastructure capital formation and capital formation in machinery and equipment. For the series on GDP and on investment in machinery and equipment, we refer to Smits, Horlings and Van Zanden (1997). Both series are displayed in constant prices in Figure 1. Because series for machinery investment are only available for the second half of the previous century, we consider the sample period 1853–1913.5

In the econometric analysis of this paper, we use capital formation figures instead of capital stocks because of the inherent problems of making capital stock estimates for infrastructural works using the standard perpetual inventory method. Although widely applied in the economic literature, Feinstein (1968) has argued that the “awkward” life cycle of infrastructural works, often without a clear date of “birth” and nearly always without a clear moment of retirement, makes them less suited for application of the perpetual inventory method. Sturm and De Haan (1995) have also shown that assumptions concerning the lifespan of capital stocks can be crucial for the results. As we do not explicitly estimate a production function, we are not forced to use capital stocks in our analysis. Furthermore, the time-series

5Data on machinery investment are available as from 1850. However, to exclude the outlying peak in infrastructural investment in 1852 caused by the reclamation of the “Haarlemmermeer,” our sample period starts in 1853.
properties of the investment series facilitate the econometrical analysis considerably, as will be seen below.

Gramlich (1994) has noticed that data limitations force economists to use public investment expenditures as a proxy for total infrastructure outlays. This may not be optimal. First of all, in many countries part of the infrastructure is financed and constructed by the private sector. Second, public investment often consists of much more than infrastructure investment alone. For instance, many governments are responsible for residential investments and spend on public buildings. Our dataset solves both problems by capturing public as well as private infrastructure investment spending.

The data on infrastructural investments are taken from Groote (1996). He gives annual time series on capital formation in current and constant prices, and subdivided by sector or type of asset. Only the truly infrastructural aspects of these sectors are included. Thus, the permanent way and works of railways are included, but rolling stock is not.

Because the definition of machinery and equipment is based on the definition of infrastructure, both series are complementary: the aggregation of investments in infrastructure and in machinery and equipment gives total capital formation, excluding residential and non-residential buildings. Machinery and equipment investment, agricultural capital formation, and work in progress are all included in the category of machinery investment.
For analytical reasons, we will divide infrastructure investments into transport infrastructure and other remaining infrastructure. Transport investments consist of main railways, light railways, (urban) tramways, canals and navigable rivers, harbours and docks, and (paved) roads. The other infrastructural sectors include: gas, electricity, water supply, the electromagnetic telegraph, (local) telephone networks, drainage, dikes, and land reclamation.

Figure 2 displays these two series and their sum, that is, total infrastructure investments, in constant 1913 prices. Except for 1860, transport infrastructure investments always exceeded other infrastructure investments.

Prior to the analysis, natural logarithms are taken from all series.

**Time-Series Properties**

The asymptotic and finite sample distributions of causality tests are sensitive to unit roots and time trends in the data series (Sims, Stock and Watson 1990; Stock and Watson 1989). The rewriting of our original VAR model, necessary to conduct impulse-response analysis and variance decomposition analysis, assumes stability of the model. A necessary condition to achieve stability is that the time series are (trend) stationary. Therefore, non-stationary variables must be transformed into stationary ones before using them in our regression analysis.
To determine whether series are stationary, we follow the testing strategy suggested by Dolado, Jenkinson and Sosvilla-Rivero (1990) and use the Augmented Dickey Fuller (ADF) test. Furthermore, we also apply the unit root test developed by Kwiatkowski et al. (1992) which has stationarity as its null hypothesis.

Table 1 reports the outcomes of both tests. Comparing the t-statistics from the ADF test and the corresponding critical values shows that all time series are trend stationary. These results are confirmed by the test of Kwiatkowski et al. (1992). Hence, we will include a trend variable in our VAR models.

As post–World War II economic time series are almost without exception non-stationary, the finding that the time series under consideration are trend stationary is in itself a remarkable result. Nelson and Plosser (1982) conclude that most post–World War II macro-economic variables are difference stationary, implying that a temporary shock has permanent effects which necessitates first-differencing, or the use of complex cointegration techniques.

However, our results for the second half of the nineteenth century clearly indicate that GDP and the investment series are trend stationary. At first sight, the trend-stationarity character of our series facilitates the mathematics. Unfortunately, trend stationarity also implies that changes in one variable do not have a permanent effect on the other variables because by definition all series ultimately return to their long-run trend paths. Therefore, the fact that our series are trend stationary is not only rather puzzling but also frustrates long-run effects of infrastructure investment. For this reason, we limit our attention in this paper to modeling the medium- and short-run effects.

4. Results

Granger-Causality Test Outcomes

Table 2 displays the results. For each equation we first show the number of lags that are included for each variable. Second, the $\chi^2$-statistic reports

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6We also used the modifications to the Dickey-Fuller unit root tests as suggested by Phillips (1987) and Phillips and Perron (1988). The conclusions are virtually the same as compared to the ADF tests and are therefore not reported.

7Filtering the trend from the individual series instead of including a trend in the regressions does not change the qualitative outcomes presented below.

8Time series over the nineteenth century for the United Kingdom prove to be trend stationary as well (Feinstein 1972, 1988).

9It is generally held that time series covering a longer time span are only stationary if one allows for structural breaks in the series concerned (De Haan and Zelhorst 1993; Zelhorst and De Haan 1995; Crafts and Mills 1997).
<table>
<thead>
<tr>
<th>Series</th>
<th>Augmented Dickey-Fuller Test</th>
<th>Kwiatkowski et al. test(^a)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Trend Constant</td>
<td>Trend Constant</td>
</tr>
<tr>
<td></td>
<td>Lags</td>
<td>(\tau^b)</td>
</tr>
<tr>
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<td>0</td>
</tr>
<tr>
<td>Mach.inv.</td>
<td>1</td>
<td>4.79**</td>
</tr>
<tr>
<td>Infra.inv.</td>
<td>0</td>
<td>3.68*</td>
</tr>
<tr>
<td>Transp. infra</td>
<td>0</td>
<td>3.88*</td>
</tr>
<tr>
<td>Other infra</td>
<td>0</td>
<td>3.62*</td>
</tr>
</tbody>
</table>

Sample: the Netherlands, 1853–1913.

\(^a\)See main text for variable definitions.

\(^b\)At a 5 (1) % significance level the MacKinnon (1991) critical values are \(-3.49 (-4.13)\) when a trend and a constant are included (\(\tau_p\)).

\(^c\)At a 5 (1) % significance level the MacKinnon (1991) critical values are \(-2.91 (-3.55)\) when only a constant is included (\(\tau_p\)).

\(^d\)The number of autoregressive lags is set at four.

\(^e\)The asymptotic critical values for the significance levels of 5 (1) % are respectively 0.146 (0.216).

\(^f\)The asymptomatic critical values for the significance levels of 5 (1) % are respectively 0.463 (0.739).

*Significant at a 5% level.

**Significant at a 1% level.
### TABLE 2. VAR-FPE Model

<table>
<thead>
<tr>
<th></th>
<th>GDP eq.</th>
<th></th>
<th></th>
<th>Machinery inv. eq.</th>
<th></th>
<th></th>
<th>Infra.inv. eq.</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>lags</td>
<td>$\chi^2$</td>
<td>sum</td>
<td>$\chi^2$</td>
<td>lags</td>
<td>$\chi^2$</td>
<td>sum</td>
<td>$\chi^2$</td>
<td>lags</td>
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<td>GDP</td>
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<td>2.17</td>
<td>0.17</td>
<td>2.17</td>
<td>0</td>
<td></td>
<td>4</td>
<td>6.74</td>
<td>−0.59</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>14.31**</td>
<td>−0.01</td>
<td>0.12</td>
<td>0</td>
<td></td>
<td>2</td>
<td>24.95**</td>
<td>0.43</td>
</tr>
<tr>
<td></td>
<td>5</td>
<td>15.35**</td>
<td>0.09</td>
<td>13.32**</td>
<td>0</td>
<td></td>
<td>1</td>
<td>39.71**</td>
<td>0.67</td>
</tr>
<tr>
<td></td>
<td>R² (adj.)</td>
<td>0.99</td>
<td></td>
<td>0.87</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

**NOTE:** Sample: the Netherlands, 1853–1913.

*See main text for variable definitions.

**Significant at 1% level.
whether all lags are significantly different from zero, that is, the test results whether or not a strong Granger-causal relationship exists. Third, we give the sum of the parameters of these lags. Finally, the table displays the outcomes of the likelihood ratio test whether these sums are significant. Links between the equations hamper interpretation of individual coefficients. Therefore, we do not report the individual coefficients. Of course, the same holds for the sums, but their signs indicate whether there is a positive or a negative relationship between the variables.

The combined coefficient of lagged machinery investment in the GDP equation is not significant, whereas the individual coefficients are. The individual coefficient estimates reveal that the first coefficient is significantly negative and the second significantly positive. Apparently, the two effects cancel out.

The effect of infrastructure investment on GDP is positive and significant at the 1% level. So our main hypothesis is confirmed: infrastructure investment is a significant explicand of GDP.

According to the FPE criterion, besides infrastructure only GDP enters the infrastructure equation. As GDP is included with four lags, there is at least a weak Granger-causal relationship from GDP to infrastructure investment which suggests that there is feedback between infrastructure and GDP. However, neither individual GDP coefficients, nor their sum, are significant. Furthermore, it should be noted that infrastructure positively Granger-causes GDP whereas the negative sign of GDP in the infrastructure equation indicates that GDP negatively Granger-causes infrastructure.\footnote{Using post–World War II data, Sturm and de Haan (1998) also report a negative effect of production on public investment in the Netherlands.}

The most striking fact from the equation for investment in machinery is that there is no relationship between investment in machinery and equipment, and infrastructural investment. This result does not confirm the hypothesis that infrastructure positively influences GDP indirectly through machinery outlays. Also business cycles, as indicated by changes in GDP, do not influence investment decisions in machinery and equipment. Only machinery investments in previous years affect this year’s investments.

To summarize, we find evidence of only three Granger causal relationships in Table 2: infrastructure positively Granger-causes GDP, machinery investment neutrally Granger-causes GDP, and GDP negatively Granger-causes infrastructure.

Especially the integration of markets that were regionally separated stimulated economic growth in the previous century. As we believe that transport infrastructure induced, or at least enabled, this integration, we split
up the infrastructure series into transport and “other” infrastructural capital spending.

As Table 3 shows, the effect of transport infrastructure on GDP is more significant than the effect of other infrastructure investments. Furthermore, a longer lag length is necessary to capture the effect of transport infrastructure compared to the other infrastructure. This might indicate a longer-lasting effect of the former on GDP. Mainly, transport infrastructure is negatively affected by GDP.

This time investment in machinery and equipment is not solely explained by its own lags. Mostly, other infrastructural investment positively influences machinery investment. Therefore, we find some evidence that other infrastructure investment might indirectly influence GDP through machinery investment.

**Impulse Responses**

To further analyze the estimated VAR model, we apply impulse-response analysis. The ordering we employ is “infrastructure,” “machinery,” “output.” Placing GDP last is consistent with the single-equation studies like Aschauer (1989) in which the other variables in the model directly affect GDP. Placement of “infrastructure” first is based on the assumption that contemporaneous shocks to infrastructure investment stem mostly from government decisions, which we consider as less endogenous than the other variables. Usually the choice of the ordering is not innocuous. Fortunately, the largest absolute correlation in our three-variable model, which is between total infrastructure and GDP, equals only 0.15, implying that the ordering of the variables is of minor importance. We experimented with other orderings. As expected, the outcomes stay roughly the same.

Figure 3 displays the impulse-response functions and their error bands for the estimated equations in Table 2. In interpreting the graphs, note that the variables are all in logarithms. Hence, a 0.01 movement corresponds to a 1% change. In addition, reading across any column, the scale on the vertical axis is the same for all shocks. These graphs allow several conclusions.

As the upper-right panel shows, the responses of the GDP-equation to a shock in infrastructure investment are highly significant. The size of the shock is such that it adds somewhat more than 18% to infrastructure investments. The maximum response of GDP is somewhat above 1% and is reached after five years. This might be interpreted as evidence that it takes some time for the system to adapt to changes in the infrastructural environment. The initial small positive effect in Figure 3 may be caused by backward linkages, or direct impulses on the economy through the demand for labor, raw materials and other capital goods when infrastructural works are con-
TABLE 3. VAR-FPE Model Using Transport and Other Infrastructure

<table>
<thead>
<tr>
<th></th>
<th>GDP eq.</th>
<th>Machinery inv. eq.</th>
<th>Other infra. eq.</th>
<th>Transport infra. eq.</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>lags</td>
<td>$\chi^2$</td>
<td>sum</td>
<td>$\chi^2$</td>
</tr>
<tr>
<td>GDP</td>
<td>1</td>
<td>0.49</td>
<td>0.08</td>
<td>0.49</td>
</tr>
<tr>
<td>Mach. inv.</td>
<td>2</td>
<td>13.41**</td>
<td>-0.02</td>
<td>0.86</td>
</tr>
<tr>
<td>Other infra.</td>
<td>1</td>
<td>5.21*</td>
<td>0.05</td>
<td>5.21*</td>
</tr>
<tr>
<td>Transp infra.</td>
<td>5</td>
<td>12.43*</td>
<td>0.06</td>
<td>10.99**</td>
</tr>
<tr>
<td>$R^2 (adj.)$</td>
<td></td>
<td>0.99</td>
<td></td>
<td>0.89</td>
</tr>
</tbody>
</table>

NOTE: Sample: the Netherlands, 1853–1913.

*a* See main text for variable definitions.

**Significant at a 10% level.

*Significant at a 5% level.

** Significant at 1% level.
Output Effects of Infrastructure Investment

Figure 3. Impulse Responses of the VAR-FPE Model (including their 95% confidence intervals)

The responses of output on shocks in infrastructure and machinery, respectively, differ in three ways. First, a growth impulse of machinery investment dies out much faster than an infrastructure impulse. After six years already, machinery investment ceases to have any effect. It takes approximately eleven years before a shock in infrastructure investment has died out. Obviously, the economy adapts more easily to changes in machinery capital. Second, the point estimates of the responses of machinery investments are on average lower than those of infrastructure. The size of the shock to the machinery and equipment equation is much larger (approximately 26%) as compared to the infrastructure equation (approximately 18%). Since machinery investment exceeds infrastructure investment most of the time, this suggests that the aggregate effect of infrastructure investment on GDP in
the period under study has been much larger. It is tempting to conclude that investing in infrastructure was a rational decision in the nineteenth century. Third, GDP decreases remarkably in the first period after a machinery shock. Apparently, the economy needs one period to adapt to the changed stock of machines.

As can be seen from the lower-left panel of Figure 3, growth of GDP has on average a negative effect on investment in infrastructure. This again supports the view of infrastructure as a prerequisite for growth, and as a large technical system, characterized by indivisibilities. When, after heavy initial investment, a certain threshold in the level of infrastructure is attained, the economy starts to grow. By then, indivisibilities will have generated an overcapacity in infrastructural services. Infrastructural investment needs are thus much smaller and will taper off, whereas GDP can continue to grow.

These results fortify the previous Granger-causality outcomes. Mainly infrastructure investment has a large effect on GDP, and it takes some time for GDP to react to changes in infrastructure.

Figure 4 displays the corresponding impulse responses in case infrastructure investment is subdivided. The ordering employed here is “transport infrastructure,” “other infrastructure,” “machinery,” “output.” As might be expected from the causality analysis, transport infrastructure causes a large rise in GDP and peaks after five years. The instantaneous impact of total infrastructure can largely be attributed to other infrastructure. Of course, this is exactly what was to be expected beforehand.

As expected from Table 3, machinery investment is largely influenced by other infrastructure. Transport infrastructure, on the other hand, does not significantly alter the course of machinery investment.

In the VAR-FPE model in which infrastructure investment is subdivided, the largest absolute correlation of 0.35 is between GDP and other infrastructure investment. Therefore, the relative ordering of GDP and other infrastructure investment might have a significant effect on our results. However, interchanging other infrastructure and GDP in the ordering hardly changes Figure 4; after one period, the responses are approximately the same as in Figure 4.

**Variance Decompositions**

As can been seen in Table 4, the forecast errors in our three-variable model of infrastructure and machinery investment are mainly due to their own shocks. In the long-run, GDP shocks can explain only 4% of the forecast error of infrastructure, whereas shocks in infrastructure investment capture hardly 1% of the forecast error of machinery investment.

On the other hand, the decompositions of the GDP forecast error as tabulated in Table 4 show that a comparatively large part is accounted for
by machinery and infrastructure investment shocks. In the long run almost 40% of the variance is explained by machinery and infrastructure investments shocks, both capturing approximately 18%. Conspicuously, machinery investment shocks already explain a large part after the first period, whereas infrastructure only significantly starts to contribute to explaining the forecast error after five periods. Again, infrastructural investments take almost five periods to have an effect.

In Table 5, the variance decomposition for our four-variable model shows that both types of infrastructure combined explain almost 30% of the forecast errors of GDP. The differences of the effect of transport and other infrastructure investment on GDP are large. While other infrastructure shocks already reach their maximum in explaining GDP variance after two years (17.3%), transport infrastructure really starts to play a role in explaining GDP variance after only five years.
<table>
<thead>
<tr>
<th>Equation</th>
<th>Innovation</th>
<th>0</th>
<th>1</th>
<th>3</th>
<th>5</th>
<th>10</th>
<th>15</th>
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**NOTE:** Sample: the Netherlands, 1853–1913.

*The forecast error variance decompositions are in percentages of the VAR-FPE model. Standard errors are shown in parentheses.*
The forecast errors of both other and transport infrastructure are mainly explained by their own shocks. Only a minor 3% of the forecast error of transport infrastructure is explained by movements in GDP. This time, however, the variance in machinery investment is for more than 17%, ultimately explained by shocks in other infrastructure investment, and around 6% of its movements are due to shocks in GDP.

5. Discussion

In this paper we have exploited a new dataset covering the second half of the nineteenth century of the Netherlands. After having determined that our series are trend stationary, we have estimated several VAR models. Using the Granger-causality test and innovation accounting, we were able to give a quantitative basis to intuitive conclusions drawn in the earlier literature on the description of the infrastructural system in the Netherlands in the nineteenth century. From all models tested here, we conclude that infrastructural investments have positively influenced output in the Netherlands in the second half of the nineteenth century.

Splitting up infrastructure investment shows that both transport investment and other infrastructural projects have contributed to the Dutch industrial revolution. Whereas transport infrastructure affects GDP after five years, other infrastructure seems to induce short-run demand effects. As transport infrastructure has a larger and longer-lasting effect on GDP, these infrastructure projects seem to have especially induced, or at least enabled, the integration of markets which were regionally and functionally separated before.

Transport infrastructure does not significantly influence machinery investment. Only other infrastructure investments seem to be related to machinery investment. Therefore, the thesis that transport infrastructure positively influences GDP indirectly, through machinery outlays, is not confirmed.

GDP is the only variable in our model that has an effect on the level of infrastructure outlays. Investments in transport infrastructure are particularly negatively affected by increases in GDP.

It is important to note that, because of the trend-stationary character of the series used, all of the above-mentioned effects are only transitory. By definition, shocks on a trend-stationary variable cannot have permanent effects. Given that most post-World War II macroeconomic variables are difference-stationary, the trend-stationary character of our series is puzzling. We conjecture that the character of output has changed over the last one and a half centuries, possibly because of infrastructure investment. Further research is necessary to support this claim.
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**NOTE:** Sample: the Netherlands, 1853–1913.

*The forecast error variance decompositions are in percentages of the VAR-FPE model using infrastructure divided into transport and other infrastructure. Standard errors are shown in parentheses.*
Of course, one has to be careful translating these findings for the past into policy recommendations. For instance, most of the investments in our dataset concern infrastructure which previously did not exist at all. The effect on the economy of an expansion of an already existing infrastructure network—as is common nowadays—might differ from that of the development of a new network. However, this study has made it clear that different types of infrastructure can have different effects on the economy. As shocks in non-transport infrastructure investment have especially shown, aggregate demand impulses cannot be ruled out beforehand. Many macroeconomic studies concentrate solely on the productivity effects of additional infrastructure investment. Therefore, it is very possible that these productivity effects tend to be overestimated.

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References


