The Impact of Technology Shocks on Hours Worked at the Industry Level: An FASVAR Approach

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Abstract

In this paper, I offer an empirical analysis of the effect of technology shocks on hours worked at the industry level. In particular, I establish the existence of aggregate technology shocks within the manufacturing sector, and investigate their effect on industry hours worked. A factor model of the cross-section of labor-productivity growth produces aggregate and industry-specific components, from which technology shocks are identified. By means of a Factor Augmented Structural Vector Autoregression (FASVAR), I demonstrate that industry hours respond differently to a manufacturing aggregate technology shock than they do to industry-specific technology shocks. The latter are viewed as more refined compared to disaggregated shocks identified in the pre-existing literature. Moreover, on average, the identified industry-specific technology shocks in this paper appear to contribute the most in the variance of labor-productivity growth, whereas the manufacturing aggregate technology shock contributes the most in the variance of hours worked. Robustness checks also reveal that the industry-specific technology shocks alter the renowned expansionary effects of inventory holdings and Total Factor Productivity shocks on hours worked.

Keywords:
Productivity, Hours, Factor-Analysis, Technology-Shocks

JEL: E24, E32

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1. Introduction

The exact nature of the relationship between hours worked and changes in productivity remains unresolved, and has attracted increased research interest over the past decade. Standard Real Business Cycle (RBC) models had earlier conjectured a positive comovement between technology improvement, output and employment. The basis of this conjecture lies both in the upward sloping labor supply curve, and a rightward shift in the labor demand curve incited by a positive technology shock. The intuition is that it is beneficial for a firm to hire more workers when the marginal product of labor outweighs the marginal cost, which is in the form of real wages. This concept was shown at least as early as in Burns and Mitchell (1946), and, later, in the seminal works of Kydland and Prescott (1982), and Long and Plosser (1983), to name a few. However, the empirical findings of Gali (1999) marked a pivotal point in the literature as they contrasted with the long-held RBC conjecture. Using a Structural Vector Autoregression (SVAR) with long-run restrictions on post-war US data, Gali found that hours worked, in the short-run, actually decline after a positive technology shock. He also uncovered that the contribution of technology shocks to the business cycle has become very minimal, a claim that seemingly put the validity of RBC models at risk. Gali’s findings were later reproduced in Shea (1999), Francis and Ramey (2002, 2009), and Gali and Rabanal (2004) amongst others. Nevertheless, there is a sub-category of research that has recently reproduced the initial findings of RBC models. The most notable in this category is Christiano et al. (2003, 2004), who point out that the short-run impact of a technology shock on hours depends on how hours are specified in a VAR model, which, in itself, relies on stationarity or unit-root assumptions for hours. Unlike Gali and the other authors who found similar results, Christiano et al. (2003) advocate the use of hours per-capita in levels through which they produce an increase in hours after a positive technology shock. In an indirect attempt to find common ground, Pesavento and Rossi (2005) apply an agnostic methodology in which the researcher does not have to impose stationarity assumptions on hours worked. Using this approach, they find that hours decline after a positive technology shock but the decline is very short-lived, especially in comparison to previous findings. Further in the direction of bridging the gap, Gospodinov et al. (2011) expand on the existence of a crucial low-frequency comovement between labor-productivity and hours, which is handled differently in levels and in first-differences, thus explaining the inconsistencies in the implications of the two models. While the levels specification incorporates this comovement when computing impulse responses, the differenced specification suppresses it to zero. Gospodinov et al. (2011)
uncover that removing the low frequency component and using long-run restrictions yield similar results for both the levels and differenced specifications of hours.

A large volume of publications studying this topic, including the above listed, focuses on the national aggregate economy yet, as argued in Reichlin (2003), modern macroeconomic theory is based on the representative agent assumption, thus a deeper understanding of the economic dynamics of micro entities such as industries is non-trivial. Moreover, substantial evidence has been presented on the heterogeneity of growth patterns at disaggregated levels of an economy. For instance, Harberger (1998) offers an empirical demonstration of the diverse productivity growth patterns observed at the firm level in US data. He argues that a proper understanding of changes in aggregate productivity calls for capturing the patterns at the grass-root (firm) level. In a different, yet relevant, context, Foerster et al. (2008) uncover that variations in the national Industrial Production Index can be explained by both aggregate and sector-specific variables. They profess that shocks to the latter fail to cancel out on aggregate, and that complementary sector-linkages may propagate sector-specific shocks throughout the economy thus generating aggregate variability. Specific to the relationship between technology shocks and employment, limited effort has been directed towards disaggregated analyses. Notable exceptions include Basu et al. (1998, 2006), who use Solow residuals from 29 industries to formulate what they profess to be a purified aggregate technology series. Upon controlling for increasing returns to scale and input utilization, they find that technology improvements cause employment to decline in the short-run. Such findings are in total agreement with those made in Gali (1999). Meanwhile Chang and Hong (2006) use a bivariate SVAR, adopting Gali’s long-run restrictions, to investigate whether improvements in an industry’s Total Factor Productivity (TFP) raises or lowers employment. Using data on US manufacturing industries, they find vastly varying patterns of responses of hours across industries, but observe that more industries exhibit a positive short-run co-movement between hours worked and TFP shocks. Holly and Petrella (2012) build up on the work of Chang and Hong (2006) by controlling for inter-sectoral linkages using a VAR with exogenous variables (VARX) that are weighted according to input-output tables ². Restrictions for their VAR are obtained from a simplified multi-sector growth model. Their findings show that after controlling for sector linkages, a positive shock to labor-productivity is expansionary with respect to hours worked.

²The existence and importance of inter-sectoral linkages has been shown in works such as Kim and Kim (2006), Horvath (1995), and Foerster et al. (2008).
In this paper, I champion the need for increased disaggregated studies for an improved understanding of the interaction between productivity changes and employment. To this objective, I seek to establish if there are any aggregate technology shocks within the US manufacturing sector, and if so, investigate how they affect hours worked in the manufacturing industries, in comparison to industry-specific technology shocks. This analysis will help shed light on the relevant stochastic dimension of productivity in the manufacturing sector. In particular, it will build on, and help bridge the gap between, the main approaches in Chang and Hong (2006) and Holly and Petrella (2012). Essentially, the former analyzes the effect of industry-specific technology shocks on industry unemployment, while the input-output channel in the latter offers a mechanism through which an industry-specific technology shock can be transmitted to other industries. My efforts are directed towards understanding the effect, on industry hours, of manufacturing aggregate shocks that simultaneously affect labor-productivity in all industries. Methodologically, I argue that relevant information regarding the variance of manufacturing labor-productivity growth is already contained in the cross-section of labor-productivity growth itself. Therefore, an appropriate aggregation of labor-productivity growth would facilitate the extraction of this information. Accordingly, I propose a factor model of manufacturing labor-productivity growth as an alternative means for estimating manufacturing aggregate shocks. This approach differs from the commonly-cited TFP-aggregation of Basu et al. (2006), and is preferable for the following reasons. Firstly, it generally compiles an aggregating index that is based on the correlation patterns in the variance of a large panel of data. This, in turn, facilitates an accurate identification of the underlying causal structure of the data. Secondly, a factor model enables the identification of multiple aggregates, rather than imposing the assumption of a single aggregate, as implicitly done in Basu et al. (2006). Thirdly, the extraction of aggregate components 'refines' the remaining industry-specific dynamics of the relationship between hours and productivity changes. Lastly, estimating manufacturing aggregates in this manner simultaneously captures the contribution of national aggregates, yet the converse would not necessarily hold.

With these points in mind, I offer a two-fold argument. Firstly, I conjecture that labor-productivity, at the industry level, is driven by both industry-specific shocks, and shocks that are common across all manufacturing industries. I substantiate this conjecture by studying the patterns of shocks identified

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3In many publications, the terms 'sector' and 'industry' are often used interchangeably. In this paper, I will take a sector to be a larger entity consisting of a group of smaller industries.
in standard bi-variate industry SVARs (of labor-productivity and hours) to detect the presence of aggregate components. Secondly, I argue that the cross-sectional scope of a technology shock (i.e. whether it is industry-specific or common across all industries) is an important determinant of the response of hours to a technology shock. By means of a Factor Augmented Structural VAR (FASVAR) methodology, I estimate unobserved common and idiosyncratic factors that drive productivity growth across all industries, and incorporate them into an SVAR model, in place of labor-productivity growth itself. Compared to a standard SVAR, this approach incorporates more pertinent information into the model, hence allows the usage of a large data set. I establish the existence of up to two aggregates for manufacturing labor-productivity growth, and up to three for Total Factor Productivity (TFP). My main findings indicate that while the responses of hours to a positive technology shock generally vary across manufacturing industries, they also display a significant variation based on the scope of the shock. Industry hours seem to increase after a positive manufacturing aggregate technology shock, whereas they decline after an idiosyncratic technology shock. Both results are robust to controlling for inventory holdings, and the latter result is robust to using TFP. In terms of importance, the idiosyncratic shocks are shown to be the most important contributor in the variance of labor-productivity growth, while the common shock appears to contribute the most in the variance of hours worked. The empirical results in this paper can be seen as motivation and a basis for the formation of relevant theoretical models.

The remainder of the paper is as follows: in the next section, I closely review selected publications on the impact of technology shocks on disaggregated hours. I also conduct benchmark industry SVARs and determine the existence of aggregate elements in the structural shocks therein. In the third section, I introduce the FASVAR general econometric framework, whereas data and specific details of the methodology are provided in section 4. The fifth section presents results from the FASVAR, while section 6 provides a discussion of my findings, supplemented by robustness checks to investigate the relevant role of inventory holdings, and the use of TFP instead of labor-productivity. Section 7 provides a conclusion.

2. A Closer Literature Review

Among the papers discussed in the introduction, Chang and Hong (2006) conduct an extensive disaggregated analysis of the topic at hand. They utilize data on 458 4-digit level manufacturing industries,
categorized under the Standard Industrial Classification (SIC), for the period 1958 - 1997. They further aggregate the data to both the 3-digit and 2-digit levels, the latter being one level below the national aggregate level. Methodologically, they perform a bivariate SVAR, using long-run restrictions as in Gali (1999), to study the short-run response of hours worked to a positive TFP shock, per industry. While the responses vary greatly, they find that the number of positive short-run responses exceeds that of negative responses at all three industry-classification levels. For comparison, they also use labor-productivity instead of TFP, and obtain more negative responses. However, they profess TFP to be the most natural measure to use since labor-productivity could reflect input-mix and efficiency changes, and therefore conclude that technology shocks are pro-cyclical with respect to hours worked.

Following Chang and Hong (2006), I conduct bivariate SVARs consisting of labor-productivity growth and hours for all industries. This exercise will serve two purposes; firstly, I will use the technology shocks identified in these SVARs to determine the existence of manufacturing aggregate components. Secondly, the results from this exercise will serve as a benchmark for eventual findings in this paper. While acknowledging the general argument for the use of TFP, I gather that using labor-productivity provides for better policy implications\(^4\). For the ease of comparison with existing literature, I utilize the NBER-CES database for US manufacturing, classified under the SIC, with two points of deviation\(^5\). Firstly, instead of gross output, I use value-added output to compute labor-productivity. This is preferable because the database uses sales (value of shipments) as a proxy for output, and gross sales do not account for material purchases. As a result, an industry’s large sales value could merely be reflective of high costs of intermediate inputs rather than the actual internal production process. The use of value-added output accounts for material (input) purchases and thus gives a more favorable account of productivity for the purpose of this paper. Secondly, the time dimension of my panel (1958-2009) is longer compared to Chang and Hong’s 1958-1997.

2.1. The Standard Bivariate VAR Model

A brief description of the empirical model used for this exercise is as follows; consider a vector \( \Delta X_t \) \([\Delta Y_{i,t}, \Delta h_{i,t}] \) where \( Y_{i,t} \) and \( h_{i,t} \) denote, respectively, labor-productivity and hours worked for industry \( i \)

\(^4\)Appendix A in Holly and Petrella (2012) presents a complete account on the use of labor-productivity versus TFP.

\(^5\)I provide a detailed description of the data in Empirical Implementation section.
at time \( t \). For any variable, \( z_t \), let \( \Delta z_t \) denote its first log-difference \(^6\). The reduced form VAR is presented as

\[
\Delta x_t = \alpha + A(L) \Delta x_{t-1} + u_t,
\]

where \( \alpha \) is a vector of constants, \( A \) is a matrix of coefficients, \( L \) is a lag operator, and \( u_t \) is a vector of reduced form residuals such that \( u_t = [u^1_t, u^2_t] \), where \( u^1_t \) are the residuals from \( \Delta y_t \), and \( u^2_t \) are the residuals from \( \Delta h_t \). Of ultimate interest are the effects of the structural shocks, \( \varepsilon_t = [\varepsilon^1_t, \varepsilon^2_t] \), which can be seen from the model's structural moving average form, \( \Delta x_t = C(L) \varepsilon_t \). Here \( C(L) \) is a 2 x 2 matrix containing the variables’ impulse responses to the structural shocks over a selected horizon, say \( k \). Although these shocks are not observable, they can be estimated from the VAR residuals through the relationship \( u_t = A_0 \varepsilon_t \), for a given square matrix \( A_0 \). To attach economic interpretations to the shocks, long run restrictions are imposed on the estimate of \( A_0 \) such that \( \varepsilon^1_t \) is the only shock that affects labor-productivity permanently. As done in Gali (1999), this is then interpreted as a technology shock. The long-run effect of the remaining shock, \( \varepsilon^2_t \), is only limited to hours worked, and this shock is conventionally identified as a non-technology shock. It could refer to disturbances stemming from the demand side of an economy.

Table 1 presents a summary of the contemporaneous responses of industry hours to the technology shocks identified above. The results are presented for all three disaggregation levels namely: 4-digit level (maximum disaggregation), 3-digit level (intermediate disaggregation) and 2-digit level (minimum disaggregation). The bold numbers indicate statistically significant responses whereas those in parentheses indicate total responses. “Negative (Positive)” denotes a contemporaneous reduction (increase) in hours, and “Industries” refers to the total number of industries contained at the specified disaggregation level. I successfully reproduce the qualitative findings of Chang and Hong (2006) i.e., responses vary across industries but the majority of them are negative. The numerical deviations arguably stem from my use of a panel with a longer time dimension, and my use of value-added output. In particular, the latter can potentially explain the emergence of relatively more positive responses in my replication.

The histograms in Figures 1-3 display the distributions of the contemporaneous impulse responses of hours. For each figure, the upper panel presents the distribution of all the contemporaneous responses

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\(^6\)At the disaggregated level, the specification of hours has not been a contentious issue, and the difference specification is prevalent.
per aggregation level, whereas the lower panel presents the distribution of only the statistically significant impact responses. Firstly, the impact responses, arguably, take the shape of a skewed normal distribution, with the skewness indicating the majority of negative responses. Secondly, it can be seen that, apart from a few outliers, the magnitude of the responses is mainly within the $[-0.1, 0.1]$ range of percent deviation, and tends to decrease as the data gets aggregated. The diminishing magnitude with aggregation is a consequence of the mixed nature of the disaggregated responses, such that aggregating simply dilutes them.

### 2.2. Aggregate Components in the Identified Shocks

Having identified structural shocks from the industry bivariate SVARs, I now explore their underlying structure, which in turn will have important implications regarding the forces driving manufacturing productivity and hours. Specifically, I seek to determine if there are any aggregate components characterizing the identified cross-section of technology series. An existence of such aggregate components would provide grounds for the decomposition of manufacturing labor-productivity growth into common and industry-specific components, which I propose in this paper. A factor model is an appropriate tool for this task as it enables the extraction of unobserved factors driving the variance of a large panel of correlated variables. Essentially, I recover the technology series from the industry SVARs discussed above, test for the number of unobserved common factors possibly underlying these series, and then extract them. Since the true common factors are unobserved, they cannot be directly extracted, but efficient estimates of the space spanned by the true factors can be obtained. In the factor modeling literature, various approaches have been proposed for this estimation. For instance, in papers such as Forni et al. (2000), Zuur et al. (2003), and Kose et al. (2003), the estimation is carried out by maximizing the joint log-likelihood of the data and the factors, conditional on the observed data. This is achieved via the Expectation-Maximization (EM) algorithm. Alternatively, if the cross-section is large enough, the true factors can be efficiently estimated non-parametrically via the use of principal components. The pioneers and strong advocates of this approach include, respectively, Stock and Watson (1998) and Bai and Ng (2002). Given the large number of industries contained in my dataset, I adopt the latter estimation method.
Fundamentally, the estimation procedure entails expressing a standardized \( N \times T \) matrix, \( Z_t \), as follows:

\[
Z_t = \Lambda F_t + e_t,
\]

where \( F_t \) denotes a vector of \( k \) common factors underlying the variance in \( Z_t \) such that \( 0 < k < N \), \( \Lambda \) is an \( N \times k \) vector of factor-loadings, and \( e_t \) denotes an \( N \times T \) vector of idiosyncratic components. The factor-loadings represent the degree to which \( Z_t \) co-moves with \( F_t \). The vector \( F_t \) itself cannot be directly estimated, but one can estimate an orthogonal vector, \( \hat{F}_t \), whose entries span the same space spanned by entries of \( F_t \). It is assumed that the common factors and the idiosyncratic components are mutually orthogonal, that is \( \mathbb{E}(F_t e_t) = 0 \). Stock and Watson (1998) proposed a non-parametric method to estimate the factors, and Bai and Ng (2002) show that, given a large enough \( N \), the factor-estimates obtained are efficient. The non-parametric method entails minimizing the following least squares criterion:

\[
\mathbb{V}_{N,T}(F_t, \hat{\Lambda}) = \frac{1}{T} \sum_{t=1}^{T} (Z_t - \hat{\Lambda} F_t)^2.
\]

It is found that (3) is consistently minimized by the principal components of \( Z_t \), which are obtained from weighted eigenvalues of the \( T \times T \) variance-covariance matrix of \( Z_t \). Under the normalization assumption that \( F_t F_t' = I \), the vector of factor-loadings matrix is estimable as \( \hat{\Lambda} = Z_t F_t / T \). An important aspect of the estimation procedure is determining the appropriate number of factors to extract. To this end, I apply a commonly used criterion proposed in Bai and Ng (2002), which is also based on the above mentioned non-parametric estimation approach. The criterion is as follows:

\[
\mathbb{IC}_2(r) = \ln \mathbb{V}_{N,T}(F_{(r)}, \hat{\Lambda}_{(r)}) - \frac{1}{N} \frac{\ln(T)}{N} \ln(\min(N,T)),
\]

where \( \mathbb{V}_{N,T}(F_{(r)}, \hat{\Lambda}_{(r)}) \) is as defined in (3) for an \( r \)-factor model, and the last term is a penalty function for over-fitting. Essentially, \( \mathbb{IC}_2 \) gives the optimal number of factors, \( k \), in a model where a maximum of \( r \) factors are extracted. For the present application, I let \( Z_t \) be the matrix of the identified industry technology shocks. As displayed in Table 2, I determine that \( k = 1 \), implying that there’s only one
aggregate component underlying the identified technology shocks. This is robust both to aggregation and to varying the values of \( r \) in the range \( 0 - 10 \). A similar conclusion is reached when \( Z \) is set to be the matrix of non-technology shocks, as \( I \) obtain \( k \) for all aggregation levels and different values of \( r \). The results are summarized in Table 2.

2.4. Comparison to a Currently Existing Aggregation Approach

The analysis of aggregate effects is not a novelty of this paper. A closely related analysis can be found in Wang and Wen (2007) who adopt the aggregation method proposed in Basu et al. (2006), which is often advocated as a means to obtain purified aggregate TFP. This aggregate measure is obtained from the residuals of sectoral production functions under the assumptions of perfect competition, constant returns to scale, and constant utilization of capital and labor. Specifically, the TFP series for industry \( i \) is obtained as \( dz_i \) in the following function:

\[
dy_i = \gamma_i(dx_i + du_i) + dz_i, \tag{5}
\]

where \( dy_i \) refers to sector \( i \)'s output change, \( dx_i \) is input change, \( du_i \) refers to unobserved changes in input utilization, and \( \gamma_i \) is the arbitrary degree of the function's homogeneity in total inputs. The aggregate TFP shock (\( dz_i \)) is then computed as the weighted sum of \( dz_i \) across \( i \). Wang and Wen (2007) further regress \( dz_i \) on both its lag and the aggregate technology shock, \( dz \), to compute sector-specific shocks. For 29 sectors, they study the average response of output and selected inputs to both aggregate and sector-specific technology shocks. They report that the difference lies mainly on the horizon i.e., aggregate shocks are contractionary in the short-run whereas sector-specific technology shocks are contractionary both in the short-run and long-run.

However, a shortcoming of this aggregation method is the inability to ensure orthogonality between the aggregate and sector-specific shocks, thus the effects of these two types of shocks might be systematically correlated. Also, the calculated aggregate shock is solely a summation of the sector-specific residuals, it does not necessarily represent unique information. The factor model approach addresses these two concerns as it produces common and idiosyncratic factors that reflect the data's underlying

\[\text{Footnote 7: Chang and Hong (2006) use the same measure but only as a robustness check. A discussion of the limitations of this measure follows below.}\]
structure, under orthogonality restrictions. Applications of factor analysis in macroeconomic contexts are not uncommon. For instance, Foerster et al. (2008) use factor analysis to study the variation in the Industrial Production index. They demonstrate that common factors account for most of the variations in the US IP index. Also, Kose et al. (2003) use factor analysis to study global, regional and country specific business cycle patterns. This paper joins the recently growing trend of researchers that merge factor analysis with Vector Autoregressions, an idea pioneered in Stock and Watson (2005). The following section provides details of the framework.

3. General FASVAR Econometric Framework

Having established evidence of a factor structure for manufacturing structural shocks, it follows that a factor model for manufacturing labor-productivity is methodologically feasible. The implication is that if structural disturbances to labor-productivity exhibit aggregate components, then labor-productivity itself should contain at least as many aggregate components. Uncovering these aggregates and investigating their effects on unemployment are among the key goals of this paper. With that in mind, an FASVAR methodology will be used to study the impact of manufacturing aggregate technology shocks on industry-level hours for the US manufacturing sector. The method originates in Bernanke et al. (2005) (henceforth BBE) in their study of the effects of monetary policy. In an attempt to capture the large volume of information utilized by policy makers, BBE estimate unobserved common factors of 120 macroeconomic variables, and use these in a VAR analysis. By studying the impulse responses of up to 5 factors, they are able to infer the effect of a monetary policy shock on the 120 macroeconomic variables. In a similar sense, I conjecture that useful information regarding the sources of variance in manufacturing labor-productivity is already contained in the cross section of the variable. The extraction and incorporation of this information into a standard SVAR model will help improve our understanding of the relationship between technology shocks and employment. Unlike BBE who extract their factors from different variables, the factors here are extracted from the same variable (labor-productivity growth) but across a panel of 451 industries. This captures unobserved aggregate forces driving productivity across all the industries that may be relevant in influencing the short-run behavior of hours. Extracting the common factors will also refine the remaining industry-specific components. Stock and Watson (2005) demonstrated in a Monte Carlo experiment that a model that merges factor analysis with VAR outperforms a standard VAR. Originally coined FAVAR in BBE, I refer to the variant method-
ology here as a Factor Augmented Structural VAR (FASVAR), and below are details of its specification.

For each industry \( i \) at time \( t \), let \( \Delta Y_{it} \) denote the growth of labor-productivity, and similarly let \( \Delta n_{it} \) denote the growth of hours worked. The issue surrounding the specification of hours in levels or first-differences is not controversial at the disaggregated level. In the pre-existing literature discussed earlier, the first-difference specification is unanimously adopted following unit root tests. For comparability, I adopt the same specification. Also, for both simplicity and compliance with pre-existing literature, I assume an economy that is exposed to only two types of shocks, namely technology and non-technology shocks. Conventionally, technology shocks are associated with the supply side of an economy, and are often identified from either labor-productivity or TFP. In this context, the technology shocks are interpreted as the permanent changes in the unobserved common factor and (later) idiosyncratic factors of labor-productivity growth. Meanwhile, non-technology shocks reflect disturbances to the economy’s demand-side elements. In estimating the FASVAR model I use the two-step approach suggested in Stock and Watson (2005) and adopted by BBE. In the first step, I utilize asymptotic principal components, as outlined in section 2.3, to estimate the common factors. After the factor estimates are obtained, they are then incorporated with hours in an SVAR model in step two\(^8\).

4. Empirical Implementation

4.1. Data

The data comes partly from the US Manufacturing Database, which is jointly prepared by the National Bureau of Economic Research (NBER) and the Census Bureau’s Center of Economic Studies (CES). It originally covers a total of 459 manufacturing industries in the United States over the period 1958-2009. However, as a result of a recent update extending the time dimension, eight industries in the database ended up each with nine missing observations, and I discarded them. These industries are Asbestos Products, Logging, Newspaper: publishing and printing, Periodicals: publishing and printing, Books: publishing and printing, Miscellaneous Publishing, Greeting Cards, and Boat Building and

\(^8\)It is important to note that a factor model of the structural shocks to labor-productivity will not necessarily resemble a factor model of labor-productivity in its entirety. As a result, the latter exhibits more common factors with aggregation as will be seen in Table 3.
Repairing. The industries in the database are classified using the 1987 Standard Industrial Classification (SIC) system. The raw data contains industries disaggregated to the 4-digit level, which is the most disaggregated level herein. The SIC was discontinued in 1997 and replaced by the North American Industrial Classification (NAIC), which accommodates more sub-industries but covers a relatively shorter time period. Among the key differences between the two is that the SIC groups industries by the output type while the NAIC groups them by the production processes. In computing labor-productivity, I take the log difference between real value-added output and total hours. Value added output is given as the shipment-value net the value of intermediate inputs. Hours are the total of production and non-production worker hours. The database only provides production-worker hours. To obtain non-production-worker hours and hence total hours worked, I follow convention in assuming that non-production workers work 2000 hours per year. Therefore, non-production hours are obtained from the product of non-production workers and 2000 hours. However, since workers are expressed in thousands while hours are in millions, it suffices to multiply by 2 rather than 2000. The growth of labor-productivity is computed as the first-difference of labor-productivity, \( \Delta Y_{it} = Y_{it} - Y_{it-1} \), where \( \{ i = 1, ..., N \} \) is the number of industries, and \( \{ t = 1, ..., T \} \) denotes time. Similarly, \( \Delta n_{it} \) denotes the log difference of total hours worked. Additional variables are the logs of end-of-year total inventory holdings, total real capital stock, and TFP. Using the criterion of Bai and Ng (2002), I determine that productivity growth at the 4-digit level is driven by a single common factor, \( F_t \) (i.e. \( k = 1 \)). To investigate the effect of aggregation, the analysis is performed at three SIC disaggregation levels. I start off with 451 4-digit industries, and then aggregate to the 3-digit level. This is achieved by grouping industries by their first two classification digits, and then summing their values. For instance, the following 4-digit industries 2011, 2013 and 2015 form the 201 3-digit industry upon aggregation. This process yields 136 industries, which are further aggregated, based on the first two digits, to produce 20 2-digit level industries. The summation is done before any computation or transformation of variables is undertaken. Additionally, data on raw material and work-in-process inventory holdings is obtained from the Bureau of Economic Analysis (BEA), and it is only available at the 2-digit industry level.

4.2. Estimation

Let \( F_t \) be the common factor of labor-productivity, and \( n_{it} \) be total hours worked. The joint dynamics of \( (F_t, \Delta n_{it}) \) are expressed via the following VAR:
\[ \Delta Y_{it} = \Delta N_{it} F_t + F_{it} + \epsilon_{it}. \]  

(6)

and the proposed factor decomposition of labor-productivity growth is as follows:

\[ \Delta Y_{it} = \Delta N_{it} F_t + F_{it} + \epsilon_{it}. \]  

(7)

The factor, \( F_t \), enters the model in levels since it is extracted from a stationary panel, \( \Delta Y_{it} \). Ng and Bai (2004) demonstrate that factors of a stationary panel are themselves stationary. The subscript, \( i \), on the factor-loadings allows each industry to respond differently to changes in the common and idiosyncratic factors. The decomposition in 7 is founded on the neoclassical multi-sector production function

\[ X_{it} = A_t Z_{it} K_{it}^{\alpha} N_{it}^{1-\alpha}. \]  

(8)

where \( X_{it} \), \( K_{it} \), and \( N_{it} \) denote output, capital stock, and labor input per sector, respectively. \( A_t \) and \( Z_{it} \) are common and sector-specific technologies. Herein, I assume that there are two types of industries: final producers and intermediate-good industries. The final producers utilize, as intermediate input, production from the latter. For simplicity, it is further assumed that intermediate-goods sectors produce their own inputs.

Equations (6) and (7) constitute the FASVAR. The last two terms on the right hand side of 7 constitute the idiosyncratic component of \( \Delta Y_{it} \), which is composed of an observed component (hours) and an unobserved component (\( \epsilon_{it} \)). Capital stock is omitted in the model application since it is commonly assumed to be constant in the short-run. As a robustness check, I included it as an additional observed idiosyncratic component in 7, and it did not alter the qualitative findings.
4.3. Step One: Factor Identification

Following BBE, in the first step of the methodology I do not exploit the fact that $\Delta n_{it}$ is observable. I rely on the demonstration in Bai and Ng (2002), and Stock and Watson (2002b) that the method of principal components, given a large enough $N$, consistently recovers the space spanned by the factors. Consequently, I extract the factor estimate, $\tilde F_t$, as the largest principal component of a demeaned and standardized $\Delta Y_t$ that minimizes (3). This yields the following

$$\Delta Y_{it} - \lambda_t \tilde F_t = \xi_{it},$$

where the term $\xi_{it}$ encompasses the space spanned by both hours worked and the unobserved idiosyncratic component $e_{it}$. The latter is recovered by running the regression

$$\xi_{it} = \lambda_{it} \Delta n_{it} + e_{it}.$$  

4.4. Step Two: SVAR Identification

In step-two I estimate the VAR in (6), where I replace $F_t$ by $\tilde F_t$, the factor-estimate obtained in step-one. I identify the structural shocks by using the Cholesky decomposition to impose long-run restrictions, as originally proposed by Blanchard and Quah (1989), and famously adopted in Gali (1999). According to these restrictions, hours can be freely affected by both technology and non-technology shocks across the model’s horizon. However, non-technology shocks are restricted from affecting productivity in the long-run. The restrictions imply that what I interpret as a technology shock is the permanent disturbance to the factors that drive productivity growth. Let $\Delta x_{it}$ denote the vector of $\{F_t, \Delta n_{it}\}$, and let the two residual terms be expressed in the vector $\eta_{it} = \{\eta_t, w_t\}$. The moving average form of (6) can be expressed as

$$\Delta x_{it} = C(L)\eta_{it},$$

\[\text{(11)}\]
where $C$ is constructed from the VAR coefficients using the canonical algorithm over the VAR horizon $k$ as follows:

$$
C_k = \left( \sum_{j=1}^{k} C_{k-j} \Phi_j \right),
$$

with $C_0 = I$.

For some matrix $Z$, the structural form is derived as:

$$
\Delta x_{zt} = D(L)\tilde{\Pi}_t,
$$

where $\tilde{\Pi}_t = Z^{-1}\pi_t$ is the vector of structural shocks, and $D(L) = Z^{-1}C(L)$ are the impulse responses, both of which are of primary interest. For the ease of notation, let $R = Z^{-1}$, and assume $RR^\varepsilon \in D$, where $\Pi^\varepsilon$ is the covariance matrix of $\tilde{\Pi}_t$. I estimate $R$ such that

$$
D(1) = C(1)R,
$$

where $D(1)$ and $C(1)$ are the cumulative sums of matrices $D$ and $C$. With the above assumptions, I get that

$$
D(1)D(1)^\varepsilon = C(1)\Sigma_k C(1)^k.
$$

Applying the lower triangular Cholesky decomposition yields the matrix

$$
D(1) = \text{Chol}[C(1)\Sigma_k C(1)^k],
$$

from which I finally obtain $R$ using (14):

$$
R = C(1)^{-1}D(1)
$$
5. Empirical Results

Using the $\text{IC}_2$ criterion of Bai and Ng (2002) discussed earlier, I estimate $k$, the optimal number of latent factors underlying the variance in labor-productivity. Table 3 shows the $k$ values for all disaggregation levels estimated using $r$ values ranging from 0 to 10. Apart from the 2-digit level, the $k$ values for labor-productivity precisely match those previously estimated for the technology shocks in the benchmark model. At the 2-digit level, the $\text{IC}_2$ criterion detects two common factors for all $r$ values in the selected range. This is not surprising for the following reasons. Firstly, the technology series from a standard SVAR represent only an identified fraction of possible disturbances to labor-productivity. Secondly, aggregating the overall data entails combining individual industries with similarities in selected characteristics, thus common factors amongst similar industries likely account for more variance when the industries are combined than when they are separate.

5.1. Manufacturing Aggregate Technology Shocks

The top panel in Table 4 reports the percentage break-down of the contemporaneous responses of industry hours after a permanent shock to the common factors underlying labor-productivity. At each disaggregation level, the second step (the SVAR) is carried out per industry hence I obtain as many total impulse responses as there are industries per level. The fifth (fourth) column of the table reports the quantities of industries that increased (decreased) hours contemporaneously after the shock. Each number is expressed as a percentage of total industries in the relevant disaggregation level. The percentages in bold refer to the quantities of statistically significant responses (hence do not necessarily add up to 100), while those in parentheses denote total increases or decreases for each disaggregation level. The third column indicates whether the responses are to a common or idiosyncratic technology shock, and the second column indicates the specification of hours. All results are based on the Impulse Response Functions (IRFs) generated from the EASVAR model. For statistical significance, 90% confidence intervals are obtained via 2000 repetitions of a bootstrap on the VAR residuals.

The results suggest that while responses vary across industries, manufacturing aggregate technology shocks are generally expansionary with respect to hours. The impact responses here, on average, contrast with those obtained from the benchmark model in section 2. In total, at the 4-digit level, hours increased in 65% of the industries, and decreased in the rest. Regarding statistically significant re-
responses. 33% of the industries had statistically significant increases, compared to 12% industries with statistically significant decreases. In both cases, there are approximately twice as many industries that increased hours as there are industries that decreased hours after the shock. This pattern is seemingly strengthened with aggregation. At the 3-digit level, there are 45% and 9% statistically significant increases and decreases, respectively. At the 2-digit level, all the statistically significant responses are increases in hours, and this applies to the two common factors detected at this level.

The frequency histogram presentations of the results in Figures 4 - 6 demonstrate the distributions and magnitudes of the responses on impact. Firstly, the negative skewness in the distributions is consistent with both the mean and median values shifting rightward in comparison to the benchmark model results. There is more variation in the magnitude of negative responses compared to the magnitude of positive responses, as seen via the close clustering of the latter while the former are more scattered. Secondly, the histograms reveal that the magnitudes of the responses in the FASVAR model appear to have shrunk, such that they are within a range of −0.1 and 0.1 percentage deviation from equilibrium, with only three outliers in total. In the benchmark model, we saw a handful of industry-responses outside this range. The reduction in magnitude provides assurance that the identified shocks are unique and not merely negative rotations of the benchmark model shocks.

5.1.1. Response Patterns in the Long-Run

The contrast in response patterns between the benchmark model and the FASVAR model is not just limited to impact responses. A closer look at the overall shape of the impulse response functions for both models reveals that the dissimilarity extends to the long-run response patterns as well. Figures 7 and 8 display graphs of the impulse response functions for the benchmark and FASVAR models, respectively, for the 2-digit level industries over 15 horizons \(^{10}\). Of particular interest are the overall shapes of the responses. In the benchmark model, a majority of the responses are hump-shaped, a characteristic that matches responses in national aggregate studies which model hours in first-differences. The implication, as seen in some industries, is that hours decline on impact and immediately recover, in a hump-shape, to levels above the initial equilibrium. However, in other industries, hours remain below

\(^{10}\)To conserve space, I do not present the other 587 graphs for the 3-digit and 4-digit levels, but they are available upon request. The graphs in Figure 8 are responses of hours after a permanent shock to the first common factor of labor-productivity at the 2-digit level.
initial levels despite the hump-shaped recovery. In the FASVAR model, these hump-shaped responses get inverted, such that hours increase and reach a peak on impact followed by a drop in the intermediate term and in the long-run. In only a few industries do we see hours permanently remaining above initial levels. Since the data used in this paper is of low frequency, the short-run responses (a minimum of a year) are very crucial for policy reactions than the long run responses. For this reason, all conclusions herein are based on short-run dynamics.

5.2. Refined Idiosyncratic Shocks

In most empirical applications of factor models where a cross-section of different variables is used, the idiosyncratic components left after the extraction of common factors hold no economic meaning, and often boil down to measurement errors. However, due to the nature of the cross section in this application, I argue that the remaining idiosyncratic components carry an economic meaning. They can be viewed as representing refined industry-specific components that drive manufacturing labor-productivity. This stems from the fact here I extract latent factors from the same variable across vastly differing industries. An assumption that each of these industries exhibit common and individualistic operational characteristics is not wild. As a result, the extraction of the common factor should lead to the identification of shocks that are more reflective of true industry-specific disturbances than those identified in the benchmark model. In the bottom panel of Table 4, I present results on the contemporaneous responses of hours after idiosyncratic technology shocks for all industries. The table shows that qualitatively, these refined idiosyncratic shocks from the FASVAR model reproduce the responses of the benchmark model. Across disaggregation levels, the majority of industries exhibit negative impact responses after a technology shock. However, the responses from the FASVAR model appear to be relatively more negative in magnitude. Again, for space conservation, I will utilize graphs of only the 2-digit level impulse response functions to demonstrate this notion. When comparing the graphs of the response functions in Figures 7 and 9, the shapes of the graphs are generally similar. This lends support to the fact that the idiosyncratic components are not merely measurement errors, but are related to the industry-specific aspect of labor-productivity. Also, the graphs from the FASVAR model are shown to be more negative at every horizon. This is evident from the downward shift in all the responses, except for only three industries; Transportation Equipment, Fabricated Metal Products, and Industrial Machines.
6. Remarks on the Identified Shocks

The identification of shocks in the FASVAR model relies heavily on the long-run identification scheme originating in Blanchard and Quah (1989), and adopted in Gali (1999) for a national aggregate analysis, and in Chang and Hong (2006) for an industry level analysis. Essentially, for each industry, disturbances to hours are restricted from affecting productivity in the long-run, yet disturbances to productivity can affect both hours and productivity at all horizons. For industry-specific shocks, the shocks identified through this scheme are generally accepted as technology shocks. The refined idiosyncratic shocks have been shown to reproduce the shapes of impulse responses from the benchmark model. Also, as seen in Figure 10, the identified shocks from both models exhibit strong similarities, with peak and trough sizes being amongst the most notable differences. This serves to show that these shocks are not merely measurement errors or trivial factor model residuals, but they are closely tied to the industry-specific component of labor-productivity. Meanwhile, for the common factor shocks to be properly interpreted as manufacturing aggregate shocks, it has to be established that they are consistent across all industries. To this end, I also present time series plots for the identified common factor shocks for all industries in Figure 11. The shocks exhibit a remarkable correlation for all levels of disaggregation. The few deviations likely stem from the fact that in the factor model, the industries are allowed to have different factor-loads hence the VAR coefficients will slightly differ. This consistency allows cross-sectional response comparisons and general conclusions about the effect of a manufacturing aggregate shock. The interpretation of this shock as a technology shocks is directly tied to the same interpretation given to a permanent labor-productivity shock.

6.1. Forecast Error Variance Decomposition

In this subsection, I compare the importance of the common and idiosyncratic technology shocks in the variances of both labor-productivity and hours worked. This is achieved via computations of forecast error variance decompositions to determine the contribution of each shock to the one-period ahead forecast error of labor-productivity and hours. The computations are done per industry, and the results are summarized in Table 5. The second column presents the percentage of industries in which the common shock contributes more than 50% of the variance in the forecast error of hours. The third column does the same for the idiosyncratic shocks. The fourth and fifth columns present the same information for the forecast error of labor-productivity. Per industry, the computations are performed
for two sets of bi-variate SVARs, one with the common factor, and another with the idiosyncratic component. The cross-model comparison done here is permissible since the second variable in each model is hours. This means that the contributions of both the common and idiosyncratic shocks have a similar reference point, which is the contribution of the non-technology shock originating in a one-time disturbance to hours. It can be seen that in a majority of industries the common technology shock contributes the most in the variance of hours worked, while the idiosyncratic shocks contribute the most in the variance of labor-productivity. This pattern only slightly gets altered at the 2-digit level. The variance decomposition results offer empirical support for the proposed factor model of labor-productivity. Having shown in earlier sections that a common technology shock yields different responses in hours, these results further show that the common technology shock arguably matters more in the variance of hours than the idiosyncratic shocks. Consequently, the factor decomposition of labor-productivity was non-trivial.

6.2. Manufacturing Aggregate Components for Hours

The non-technology shocks from the benchmark model revealed only one underlying aggregate component. In turn, the IC2 criterion on hours worked detects two underlying common factors. However, the second factor has a correlation of -0.7 with the first common factor that underlies labor-productivity, which underscores the co-movement between the two main variables in this study. In this subsection, I run a bivariate-SVAR of the first common factors of both labor-productivity and hours. This will serve to explore the manufacturing aggregate dynamics of both variables. Importantly, this exercise will help confirm whether the identified manufacturing aggregate shock above has the characteristics of a national aggregate technology shock with respect to aggregate hours. Graphs for the impulse response functions are displayed in Figure 12, and they clearly replicate results usually obtained from national aggregate data. The factor for hours declines after a permanent shock in the factor for productivity. This offers support that the identified permanent disturbance to the common factor is, at the very least, closely linked a technology shock. Its contemporaneous effect on hours differs when looking at aggregate responses versus industry-specific responses.
7. Discussion and Robustness Checks

The results discussed above reveal that the decomposition of labor-productivity into its unobserved factors, is a non-trivial exercise as it yields some suggestive results. In particular, it reveals that permanent disturbances to labor-productivity can be both contractionary and expansionary with respect to the growth rate of hours, depending on the scope of the disturbance. In the manufacturing sector, the expansionary effect is linked to manufacturing aggregate dynamics, whereas the contractionary effect manifests itself through industry-specific dynamics. This prompts the suggestion that in a standard VAR model of labor-productivity and hours, it could be that the results are dominated by the industry-specific dynamics. This could result from the VAR largely identifying shocks to the idiosyncratic component, and disregarding the common components. In the current analysis, this is avoided through the orthogonality restrictions imposed on $F_t$ and $e_t$ in step-one to ensure a truly unique effect from each component, unlike those obtained in Wang and Wen (2007). This analysis also ensures a more refined industry-specific component, especially in comparison to the one used in Chang and Hong (2006).

The economic intuition behind the results is consistent with, and can arguably form the basis to the input-output channel. According to this channel, the effects of productivity changes in an industry, A, whose output is used as an input in another industry, B, will be transmitted onto the latter industry. In a flexible-price environment, this occurs via output and price changes in these industries. From the perspective of the input-supplier, my analysis offers an improved understanding of the effect, with respect to hours, of an industry-specific change in productivity before it gets transmitted to the input-demanding industries. And from the input-demanding's perspective, the analysis can illuminate its true response upon the transmission of the effect. For demonstration, let's imagine a one-time positive technology shock only to industry A. Since industry B's productivity does not change, it will not increase its demand for A's output hence A's output will stay constant. Due to the shock and all else constant, A will now afford to produce its required output to supply to B with reduced labor input hence it will have to lay off some idle workers. On the other hand, let’s imagine a positive technology shock only to industry B. All else constant, i.e. unchanged input prices and demand for B's output, industry B will not alter its output either. Instead, it will meet its production requirement with fewer workers hence some idle workers will have to be laid off. These two instances demonstrate why idiosyncratic shocks could yield a decline in hours, as seen in a majority of industries in the FASVAR model. The eventual increase in hours in the intermediate and long-run could potentially
be explained by the slow diffusion of the positive technology shock as other industries adopt the new innovations. Meanwhile, if both A and B experience a common positive productivity shock, then B will demand more input from A to capitalize on its own productivity improvement. Furthermore, if B lowers its price it can outsell competition and will further increase output to maximize revenues. Industry A will increase output to meet the increased demand from B. All these events combined yield an overall increase in hours worked in each industry, hence the expansionary effect of the permanent manufacturing aggregate shock observed in the empirical model.

Policy implications from this work could be tied to the projected future direction of production processes, especially in manufacturing. If most production processes appear to be converging, likely due to similarities in new capital, technologies and management approaches, then more emphasis ought to be placed on understanding the impact of manufacturing aggregate shocks as their impact differs from industry-specific shocks. Whereas, if research and development and finer specializations result to diverging production methods, then industry-specific dynamics should receive more attention for optimal productivity and minimal unemployment.

7.1. The Role of Inventories: A Robustness Check

In the example provided above, outcomes could likely change if the industries’ inventory holdings are accounted for. For instance, industry A could potentially increase output after an idiosyncratic positive technology shock, if it can keep the surplus as inventory. In this section I investigate whether an industry’s ability to hold inventories alters the contemporaneous response of its hours to a positive technology shock in the FASVAR model. Inventories are generally used by businesses for production-smoothing, and stock-out avoidance. The earlier refers to the accumulation of intermediate-good inventories in preparation for a period of lower supply. This ensures continuity in the production process especially when it is in consecutive chains. Stock-out avoidance refers to the accumulation of final-good inventories in low demand periods to ensure sufficient supply in high demand periods. The intuition, as already introduced, is that if industries can keep additional output as inventories, then they can afford to increase production after a productivity improvement regardless of current external demand dynamics. This in turn could facilitate an increase in employment after a positive technology shock. At the national aggregate level, changes in inventory investment have been shown to impact on an economy’s gross domestic product (GDP), and are documented as substantial contributors to business cycle dy-
namics. A commonly held conjecture, pioneered in papers by McConnell (2000), Blanchard and Simon (2001), and Kahn et al. (2000), states that inventories played a major role in the US Great Moderation, a period of steady decline in output volatility observed in the mid-1980s. For a disaggregated analysis, Chang et al. (2009) (henceforth CHS) propose a theoretical model that introduces inventories to the standard Taylor (1980)-type model of staggered prices. Their model predicts that firms with inventory holdings increase employment after a technology shock, even under sticky prices. Using US manufacturing data, they produce largely positive responses of hours after a positive technology shock, confirming their model’s prediction. They further cite demand elasticity, and product durability as additional contributing factors to the positive responses of hours worked.

In light of the negative responses of hours to refined idiosyncratic shocks in the FASVAR model, I explore the role, if any, of inventories in the response of hours worked to an improvement in productivity. In effect, I ask whether inventory holdings can overturn these negative responses as they were shown to do under sticky-prices in CHS? If inventories can overcome the contractionary effect of sticky prices, then one would expect them to easily yield positive responses under flexible prices. A failure to do so would add substance to the decomposition of labor-productivity as a means to refine the effect of industry-specific shocks on hours. I investigate this notion using the FASVAR model, where step-two becomes a tri-variate SVAR consisting of a factor of productivity (common and later idiosyncratic), hours worked, and real inventory holdings. This step is represented as follows:

\[
\begin{align*}
F_t &= \Phi_{11} F_{t-1} + \Phi_{12} F_{t-2} + \Phi_{13} F_{t-3} + \Phi_{21} \Delta n_{it} + \Phi_{22} \Delta n_{it-1} + \Phi_{23} \Delta n_{it-2} + \Phi_{31} \Delta m_{it} + \Phi_{32} \Delta m_{it-1} + \Phi_{33} \Delta m_{it-2} + \eta_t + \nu_t,
\end{align*}
\]

where \( \Delta m_{it} \) denotes the log-difference of real total inventories. I only report findings for the differenced specification of hours for direct comparison with CHS. I use both the common and idiosyncratic factors of productivity in the SVAR. In step-one, real inventories are included as an additional observable such that regression 10 produces \( \mathbf{e}_t \) as the idiosyncratic factor, as shown below:

11 See, for instance, Blinder (1981) and Hornstein (1998)
12 Gali (1999) uses the standard sticky price intuition to explain the negative response of hours he obtained.
\[ \xi_t = \lambda_{in} \Delta n_{it} + \lambda_{im} \Delta m_{it} + \epsilon_t. \] 

I maintain the same assumption that the economy is only faced with two kinds of shocks, namely a technology shock, \( n_{it} \), and non-technology shocks, (\( w_{it} \) and \( v_{it} \)). I augment the long-run restrictions by assuming that the factor of productivity used is not affected by either hours or inventories in the long-run, whereas inventories do not affect hours in the long-run. Additionally, both hours and inventories are permanently affected by the productivity factor. Thus a Cholesky decomposition, as used earlier, is sufficient to attain these restrictions.

7.1.1. FASVAR Results with Inventories

The results from the above exercise are reported in Table 6. The top panel displays responses after a permanent shock to the manufacturing aggregates, and the bottom panel displays responses after idiosyncratic technology shocks. According to the results, permanent shocks to the manufacturing aggregates tend to increase hours in a majority of industries. This applies to both total and statistically significant responses, and the pattern seemingly gets strengthened by aggregation. These results do not show much difference to the case without inventories, in particular, the total responses remain almost unchanged. It is thus difficult to argue for any impact of inventory holdings on the response of hours to permanent manufacturing aggregate shocks. Regarding the refined idiosyncratic shocks, two observations are noted. Firstly, the majority of responses are decreases in hours. Secondly, the inclusion of inventories seems to yield even more industries with decreased hours. Both the percentages for total and statistically significant decreases are larger with inventories than without. Also, the percentages for total increases are smaller with inventories than without. It seem that inventory holdings fail to overcome the contractionary effect of the refined industry-specific technology shocks identified in the FSVAR model. It could be that in most cases, an industry’s own ability to hold inventories is, alone, not sufficient for that industry to significantly increase output and hence employment in the short run. Instead, for an input supplier who holds inventories to increase output, it would call for the input-demanders to be able to hold inventories as well. This would call for coincidental inventory holding abilities or manufacturing aggregate shocks such as general declines in storage costs.
7.2. Output vs Input Inventories

The literature on inventory investment can be generally classified into two categories. One focuses on the use of final-good inventories for the purpose of stock-out-avoidance, and it has received abundant attention. The other, which had mostly been neglected, incorporates the stage-of-fabrication linkages within and between firms where input inventories are utilized for production-smoothing. Input inventories, conventionally defined as raw materials and work-in-process products, arise whenever there is a gap between the delivery and use of inputs. They had been neglected in earlier models because their importance was largely observable in durable goods, and earlier models commonly excluded such goods. However, the significance of input inventories in production and business dynamics has been pointed out in recent work. Humphreys et al. (2001), for instance, show that input inventories are larger and fluctuate more than finished-good inventories in US manufacturing. Findings in Herrera and Pesavento (2005) show that at the disaggregated level, input and output inventories contributed differently to the reduction in output volatility during the Great Moderation. Tsoukalas (2005) states that since the usage of input materials is a factor of production, decisions on production-smoothing and output-inventory are inherently related to input-inventory decisions. Erginlu and Hofer (2011) investigate the contribution of the different inventory types to a firm's financial performance, and find that Raw Material inventories contribute the most compared to Work-in-Process and Final Good inventories. Meanwhile, Lieberman and Demeester (1999) uncover a negative correlation between productivity growth and input inventories, particularly Work-in-Process (WIP). Their key argument is that reducing WIP exposes production problems on the shop floor, enabling them to be attended to hence boosting productivity. In turn, an increase in productivity leads to a further reduction in the need for WIP.

From these publications arises the motivation to disintegrate my inventory variable into its different components, and investigate whether they have different effects on the relationship between hours and productivity. The US manufacturing data on input inventories is only available for 2-digit level industries. I run the FASVAR second step, with total inventories replaced, in turns, by Final Goods (FG), Work-in-Process (WIP) and Raw Material (RM) inventories. I present the results on the last three rows of each panel in Table 6. Regarding a shock to $F_t$, none of the inventory components yields negative hour-responses. Meanwhile, an idiosyncratic shock produces some interesting variations.

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13See Blinder and Maccini (1991) for a summary of earlier literature.
Firstly, input inventories (RM and WIP) produce more total industries with increased hours than those with decreased hours. WIP yields 60% while RM yield 55%. Meanwhile, output-inventories exhibit a more expansionary effect, with 60% total industries with increased hours. Secondly, while all inventory components produce more statistically significant increases, WIP has the least percentage. Based on statistical responses, the overall conclusions in this paper do not change after decomposing inventories. However, one can note a slight contractionary effect from input-inventories, especially WIP. This could be associated with the asserted negative relationship between productivity and WIP, which would imply that an accumulation of WIP tends to counter the initial improvement in productivity, aiding the contractionary effect of the shock.

7.3. Estimation with Total Factor Productivity

Some concern has been raised on the identification of technology shocks from labor-productivity. A noteworthy argument is made in Chang and Hong (2006) that permanent changes in labor-productivity could originate from changes in efficiency and input-mix. In support of their argument, they cite the lack of co-integration between labor-productivity and Total Factor Productivity (TFP). However, Holly and Petrella (2012) are able to demonstrate that in a multi-sector environment, permanent shocks to labor-productivity do reflect changes in TFP, either in the current sector itself or in another one via relative price changes. Owing to these exchanges, I apply the FASVAR methodology using Manufacturing TFP instead of labor-productivity, as a robustness check exercise. I start by running a standard SVAR of TFP and total hours worked, from which I determine that the identified technology shocks exhibit one underlying manufacturing aggregate component at the 4-digit and 3-digit levels, but three aggregate components at the 2-digit level. These numbers directly translate to the number of manufacturing aggregates underlying TFP itself. Table ?? summarizes the results from the benchmark and FASVAR models using TFP. The benchmark results clearly suggest that permanent shocks to TFP are generally expansionary with respect to hours. This conclusion is consistent with the main findings in Chang and Hong (2006). However, results from the FASVAR model reveal that the expansionary effect of a permanent TFP shock gets reversed upon decomposing TFP into common and idiosyncratic components. Permanent shocks to both the manufacturing TFP aggregates and the refined idiosyncratic TFP series yield more total and statistically significant increases in hours for all disaggregation levels. This differs from the case of labor-productivity where only the manufacturing aggregate shock reversed
8. Conclusion

With this analysis, I uncovered the existence of manufacturing aggregate technology shocks, and explored their short-run impact on hours worked at the industry level. I proposed a factor model to enable the decomposition of labor-productivity into unobserved common and idiosyncratic components. I argue that this decomposition offers an informative manufacturing aggregate that is based on the underlying structure of the variance in labor-productivity. It also yields a refined industry-specific component from which the true impact of an idiosyncratic shock can be studied. Both aspects are an improvement to approaches in the current literature. Using a Factor Augmented Structural Vector Autoregression, I find that while the responses of hours to a technology shock generally vary across industries, they also show an important variation based on the scope of the shock. My findings show that industries respond differently to a common technology shock than they do to an industry-specific technology shock. Notably, after a common technology shock, most industries tend to increase the amount of hours worked on impact, while the opposite case holds after an idiosyncratic technology shock. The mechanisms through which these effects manifest themselves could be linked to the input-output channel widely discussed in the literature. I conjecture that my findings shed light on the basis through which this channel works. In particular, my analysis offers an improved understanding of how an industry responds to technology shocks of different scopes before it transmits the shock to other industries via intermediate input sales. While refining the industry-specific shocks does not alter the direction of responses from the benchmark model, it alters the magnitude of responses. Additionally, the refined component seemingly resists the expansionary effect of inventories on hours that has been previously noted in the literature. A rather puzzling effect of refining the idiosyncratic component is that it also resists the established expansionary effect of TFP on hours. Upon removal of the aggregate component, hours decline after a positive TFP shock. The findings in this paper do not necessarily contradict or alter existing conclusions at the national aggregate level. However, they offer an interesting perspective on the micro-foundations of these conclusions. As we experience rapid technological advances and specializations, production processes could either converge or diverge in the future. Either outcome will have implications on the importance of common and industry-specific disturbances to productivity. In order to make policies that will benefit industries, it is crucial to fully understand the effects of such shocks, and, policy-wise,
my empirical study makes a contribution in that direction. Lastly, the findings herein could be used to motivate theoretical multisector models to explain the contrasting effects of aggregate and idiosyncratic technology shocks in the business cycle. Potential extensions to this work include exploring possibilities for economic interpretation of the manufacturing aggregates established herein. Also, the refining effect of the methodology used here could be useful in the estimation of non-neutral technology changes such as investment specific technology shocks.
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9. Figures and Tables

Figure 1: Two-digit level (20 Industries): A Frequency Histogram of Impact Responses of Hours after a Permanent Shock to Labor-Productivity

Figure 2: Three-digit level (136 Industries): A Frequency Histogram of Impact Responses of Hours after a Permanent Shock to Labor-Productivity
Figure 3: Four-digit level (451 Industries): A Frequency Histogram of Impact Responses of Hours after a Permanent Shock to Labor-Productivity

Figure 4: 2-digit level (20 Industries): A Frequency Histogram for Impact Responses of hours to a Positive Manufacturing-Aggregate Technology Shock
Figure 5: 3-digit level (136 Industries): A Frequency Histogram for Impact Responses of hours to a Positive Manufacturing-Aggregate Technology Shock

Figure 6: 4-digit level (451 Industries): A Frequency Histogram for Impact Responses of hours to a Positive Manufacturing-Aggregate Technology Shock
Figure 7: Two-digit level (20 Industries): Impulse Response Functions of Hours to Technology Shocks in the Benchmark Model

Figure 8: Two-digit level (20 Industries): Impulse Response Functions of Hours to a Positive Manufacturing-Aggregate Technology Shock
Figure 9: Two-digit level (20 Industries): Impulse Response Functions of Hours to Refined Idiosyncratic Technology Shocks

Figure 10: Time Series Plots of the Identified Idiosyncratic Shocks from the FASVAR and the Benchmark Models for all Industries
Figure 11: Plots of the Identified Manufacturing-Aggregate Technology Series for all Industries

Figure 12: Impulse Response Functions from an Overall Manufacturing VAR

Notes: The impulse responses are from a bivariate VAR consisting of the first common factor of labor-productivity and the first common factor of hours worked. The outer lines (red and green) are 90% confidence intervals obtained via bootstrap on the residuals.
Table 1: Percentages of Industries with Contemporaneous Increases/Decreases in Hours after a Permanent Shock to Labor-Productivity

<table>
<thead>
<tr>
<th>Disaggregation Level</th>
<th>Total Industries</th>
<th>Negative</th>
<th>Positive</th>
<th>Negative</th>
<th>Positive</th>
<th>Total Industries</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>451</td>
<td>39 (69) %</td>
<td>9.5 (31) %</td>
<td>38 (77) %</td>
<td>3.7 (23)%</td>
<td>458</td>
</tr>
<tr>
<td>4-digit</td>
<td>136</td>
<td>37 (66) %</td>
<td>8.1 (34) %</td>
<td>43 (82) %</td>
<td>4.2 (18)%</td>
<td>140</td>
</tr>
<tr>
<td>2-digit</td>
<td>20</td>
<td>40 (70) %</td>
<td>0 (30) %</td>
<td>45 (90) %</td>
<td>0 (10)%</td>
<td>20</td>
</tr>
</tbody>
</table>

Notes: The figures in bold refer to statistically significant impact responses, while in parentheses are total impact responses. Statistical significance is determined by 90% confidence bands obtained via a bootstrap on the residuals.

Table 2: The Optimal Number of Detected Common Factors Underlying the Identified Manufacturing StructuralShocks

<table>
<thead>
<tr>
<th>Industry Level</th>
<th>Technology Shocks</th>
<th>Non Technology Shocks</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>r 0-3 r 4-10</td>
<td>r 0-3 r 4-10</td>
</tr>
<tr>
<td>4-digit</td>
<td>1   1</td>
<td>1 1</td>
</tr>
<tr>
<td>3-digit</td>
<td>1   1</td>
<td>1 1</td>
</tr>
<tr>
<td>2-digit</td>
<td>1   1</td>
<td>1 1</td>
</tr>
</tbody>
</table>

Table 3: Optimal Numbers of Common Factors Underlying Manufacturing labor-productivity

<table>
<thead>
<tr>
<th>Industry Level</th>
<th>r 0-3 r 4-10</th>
</tr>
</thead>
<tbody>
<tr>
<td>4-digit</td>
<td>1 1</td>
</tr>
<tr>
<td>3-digit</td>
<td>1 1</td>
</tr>
<tr>
<td>2-digit</td>
<td>2 2</td>
</tr>
</tbody>
</table>
Table 4: Percentages of Industries with Contemporaneous Increases/Decreases in Hours after Positive Technology Shocks in the FASVAR Model.

Responses to a Manufacturing-Aggregate Technology Shock

<table>
<thead>
<tr>
<th>Disaggregation Level</th>
<th>Specification of Hours</th>
<th>Shock Origin</th>
<th>Decreases</th>
<th>Increases</th>
</tr>
</thead>
<tbody>
<tr>
<td>4-digit</td>
<td>Differences</td>
<td>$F_1$</td>
<td>12 (35) %</td>
<td>33 (65) %</td>
</tr>
<tr>
<td>3-digit</td>
<td>Differences</td>
<td>$F_1$</td>
<td>9 (28) %</td>
<td>45 (72) %</td>
</tr>
<tr>
<td>2-digit</td>
<td>Differences</td>
<td>$F_{t1}$</td>
<td>0 (20) %</td>
<td>55 (80) %</td>
</tr>
<tr>
<td></td>
<td></td>
<td>$F_{t2}$</td>
<td>0 (5) %</td>
<td>85 (95) %</td>
</tr>
</tbody>
</table>

Responses to Idiosyncratic Technology Shocks

<table>
<thead>
<tr>
<th>Disaggregation Level</th>
<th>Specification of Hours</th>
<th>Shock Origin</th>
<th>Decreases</th>
<th>Increases</th>
</tr>
</thead>
<tbody>
<tr>
<td>4-digit</td>
<td>Differences</td>
<td>Idiosyncratic</td>
<td>20 (65) %</td>
<td>5 (35) %</td>
</tr>
<tr>
<td>3-digit</td>
<td>Differences</td>
<td>Idiosyncratic</td>
<td>31 (78) %</td>
<td>4 (22) %</td>
</tr>
<tr>
<td>2-digit</td>
<td>Differences</td>
<td>Idiosyncratic</td>
<td>65 (90) %</td>
<td>5 (10) %</td>
</tr>
</tbody>
</table>

Notes: The figures in bold refer to statistically significant impact responses, while in parentheses are total impact responses. Statistical significance is determined by 90% confidence bands obtained via a bootstrap on the residuals.

Table 5: Percentages of industries where each shock is dominant in regards to variance decomposition.

<table>
<thead>
<tr>
<th>Industry Level</th>
<th>Contribution to Hours Forecast-error</th>
<th>Contribution to Productivity Forecast-error</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Common Shock</td>
<td>Idiosyncratic Shock</td>
</tr>
<tr>
<td>4-digit</td>
<td>67 %</td>
<td>33 %</td>
</tr>
<tr>
<td>3-digit</td>
<td>60 %</td>
<td>40 %</td>
</tr>
<tr>
<td>2-digit-$F_{t1}$</td>
<td>40 %</td>
<td>60 %</td>
</tr>
<tr>
<td>2-digit-$F_{t2}$</td>
<td>60 %</td>
<td>40 %</td>
</tr>
</tbody>
</table>

Notes: Essentially, FEVD values for both shocks are computed per industry. The numbers above indicate the proportion of industries in which either the common shock or idiosyncratic shocks had FEVD values above 30%.
<table>
<thead>
<tr>
<th>Disaggregation Level</th>
<th>Specification of</th>
<th>Shock Origin</th>
<th>Decreases</th>
<th>Increases</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Hours</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>4-digit</td>
<td>Differences</td>
<td>$F_t$</td>
<td>13 (33) %</td>
<td>43 (67) %</td>
</tr>
<tr>
<td>3-digit</td>
<td>Differences</td>
<td>$F_t$</td>
<td>8 (28) %</td>
<td>51 (72) %</td>
</tr>
<tr>
<td>2-digit</td>
<td>Differences</td>
<td>$F_t^1$</td>
<td>5 (20) %</td>
<td>60 (80) %</td>
</tr>
<tr>
<td></td>
<td></td>
<td>$F_t^2$</td>
<td>0 ( 5 ) %</td>
<td>90 (95) %</td>
</tr>
<tr>
<td>FG</td>
<td>Differences</td>
<td>$F_t$</td>
<td>0( 0 ) %</td>
<td>90(100) %</td>
</tr>
<tr>
<td>WIP</td>
<td>Differences</td>
<td>$F_t$</td>
<td>0( 0 ) %</td>
<td>75(100)%</td>
</tr>
<tr>
<td>RM</td>
<td>Differences</td>
<td>$F_t$</td>
<td>0( 0 ) %</td>
<td>85(100)%</td>
</tr>
</tbody>
</table>

**Hours’ Responses to Idiosyncratic Shocks**

<table>
<thead>
<tr>
<th>Disaggregation Level</th>
<th>Specification of</th>
<th>Idiosyncratic</th>
<th>Decreases</th>
<th>Increases</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Hours</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>4-digit</td>
<td>Differences</td>
<td>Idiosyncratic</td>
<td>37 (73) %</td>
<td>7 (27) %</td>
</tr>
<tr>
<td>3-digit</td>
<td>Differences</td>
<td>Idiosyncratic</td>
<td>51 (81) %</td>
<td>6 (19) %</td>
</tr>
<tr>
<td>2-digit</td>
<td>Differences</td>
<td>Idiosyncratic</td>
<td>80 (95) %</td>
<td>5 ( 5 ) %</td>
</tr>
<tr>
<td>FG</td>
<td>Differences</td>
<td>Idiosyncratic</td>
<td>10 (40)%</td>
<td>30 (60)%</td>
</tr>
<tr>
<td>WIP</td>
<td>Differences</td>
<td>Idiosyncratic</td>
<td>10 (60)%</td>
<td>25 (40)%</td>
</tr>
<tr>
<td>RM</td>
<td>Differences</td>
<td>Idiosyncratic</td>
<td>10 (55)%</td>
<td>35 (45)%</td>
</tr>
</tbody>
</table>

*Hours are in first differences. Bold figures are statistically significant at the 90% confidence interval, while those in parentheses refer to total responses.*
<table>
<thead>
<tr>
<th>Code</th>
<th>Industry Description</th>
<th>Code</th>
<th>Industry Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>201</td>
<td>Meat Products</td>
<td>238</td>
<td>Miscellaneous Apparel and Accessories</td>
</tr>
<tr>
<td>202</td>
<td>Dairy Products</td>
<td>282</td>
<td>Plastic Materials and Synthetic Products</td>
</tr>
<tr>
<td>203</td>
<td>Canned Preserved F and V</td>
<td>239</td>
<td>Miscellaneous Fabricated Textiles</td>
</tr>
<tr>
<td>204</td>
<td>Grain Mill Products</td>
<td>241</td>
<td>Logging</td>
</tr>
<tr>
<td>205</td>
<td>Bakery Products</td>
<td>242</td>
<td>Sawmills and Planing Mills</td>
</tr>
<tr>
<td>206</td>
<td>Sugar and Confectionery Products</td>
<td>243</td>
<td>Mill-work and Structural Wood Members</td>
</tr>
<tr>
<td>207</td>
<td>Fats and Oils</td>
<td>244</td>
<td>Wood Containers</td>
</tr>
<tr>
<td>208</td>
<td>Beverages</td>
<td>245</td>
<td>Wood Bldg and Mobile Homes</td>
</tr>
<tr>
<td>209</td>
<td>Miscellaneous Food prep-</td>
<td>249</td>
<td>Miscellaneous Wood Products</td>
</tr>
<tr>
<td>211</td>
<td>Cigarettes</td>
<td>252</td>
<td>Office Furniture</td>
</tr>
<tr>
<td>212</td>
<td>Cigars</td>
<td>251</td>
<td>Household Furniture</td>
</tr>
<tr>
<td>213</td>
<td>Chewing and Smoking Tobacco and Snuff</td>
<td>253</td>
<td>Public Bldg and Furniture</td>
</tr>
<tr>
<td>214</td>
<td>Tobacco Stemming and Redrying</td>
<td>254</td>
<td>Partitions Office and Store Fixtures</td>
</tr>
<tr>
<td>221</td>
<td>Broadwoven Fabric Mills, Cotton</td>
<td>259</td>
<td>Miscellaneous Furniture and Fixtures</td>
</tr>
<tr>
<td>222</td>
<td>B.W Fabric Mills- fiber and Silk</td>
<td>261</td>
<td>Pulp Mills</td>
</tr>
<tr>
<td>223</td>
<td>B.W Fabric Mills, wool</td>
<td>262</td>
<td>Paper Mills</td>
</tr>
<tr>
<td>224</td>
<td>B.W Smallwares Mills Combined</td>
<td>263</td>
<td>Paperboard Mills</td>
</tr>
<tr>
<td>225</td>
<td>Knitting Mills</td>
<td>265</td>
<td>Paperboard Containers and Boxes</td>
</tr>
<tr>
<td>226</td>
<td>Dyeing and Finishing Textiles</td>
<td>267</td>
<td>Converted Paper and paperboard products</td>
</tr>
<tr>
<td>227</td>
<td>Carpets and Rugs</td>
<td>271</td>
<td>Newspapers;Publishing and Printing</td>
</tr>
<tr>
<td>228</td>
<td>Yarn and Thread Mills</td>
<td>272</td>
<td>Periodicals; Publ. and Printing</td>
</tr>
<tr>
<td>229</td>
<td>Miscellaneous Textile Goods</td>
<td>273</td>
<td>Books</td>
</tr>
<tr>
<td>231</td>
<td>Men and boys’ suits Coats</td>
<td>274</td>
<td>Miscellaneous Publishing</td>
</tr>
<tr>
<td>232</td>
<td>Men-boys’ Furnishings Work gear</td>
<td>275</td>
<td>Commercial Printing</td>
</tr>
<tr>
<td>233</td>
<td>Women’s Outerwear</td>
<td>276</td>
<td>Manifold Business Forms</td>
</tr>
<tr>
<td>234</td>
<td>Women-Children’s Undergarments</td>
<td>277</td>
<td>Greeting Cards</td>
</tr>
<tr>
<td>235</td>
<td>Hats Caps and Millinery</td>
<td>278</td>
<td>Blankbooks Loose-leaf Binders etc.</td>
</tr>
<tr>
<td>236</td>
<td>Girls-Children’s Outerwear</td>
<td>279</td>
<td>Service Printing industries</td>
</tr>
<tr>
<td>237</td>
<td>Fur Goods</td>
<td>281</td>
<td>Industrial Inorganic Chemicals</td>
</tr>
</tbody>
</table>
282 Plastic Materials and Synthetic Products
283 Drugs
284 Cleaning Preps and Toiletries
285 Paints, Enamels etc.
286 Industrial Organic Chemicals
287 Agric. Chemicals
289 Miscellaneous Chem Precls
291 Petroleum Refining
295 Asphalt Paving and Roofing
299 Miscellaneous Coal and Petrol Products
301 Tires and Inner Tubes
302 Rubber and Plastic Footwear
305 Gaskets and Sealing Devices
306 Fabricated Runner Products
308 Miscellaneous Plastic Products
311 Leather Tanning and Finishing
313 Boot and Shoe Cut Stock
314 Footwear not Rubber
315 Leather Gloves and Mittens and Handling Machinery
316 Luggage
317 Handbags and Personal Leather Goods
319 Other Leather Goods
321 Flat Glass
322 Pressed-Blown Glassware
323 Products from Purchased Glass
324 Cement and Hydraulic
325 Structural Clay Products
326 Pottery Products
327 Concrete and Plaster Products
328 Cut Stone and Stone Products
329 Asbestos and Nonmetal Products
367 Electronic Components and Accessories
369 Misc Electrical Machinery Eqpt.
371 Motor Vehicle and Eqpt.
372 Aircraft and Parts
373 Ship Boat Bldg and Repairs
374 Railroad Eqpt.
375 Motorcycles Bikes and Parts
376 Guided Missiles and Space
379 Misc Transportation Eqpt.
381 Search Navigation and Eqpt.
384 Surgical Medical Instruments
331 Steel Works Furnaces etc.
332 Iron and Steel Foundries
333 Primary Smelting N.F. Metals
334 Sec N.F. Smelting
335 Extruding N.F. Metals
336 Nonferrous Foundries
339 Miscellaneous Prim Metal Products
341 Metal Cans and shipping Containers
342 Cutlery and General Hardware
343 Heating Eqpt.
344 Fabricated Structures Metal Products
345 Screw Machine Products
346 Metal Forgings and Stampings
347 Coating and Allied Services
348 Ordnance and Accessories
349 Miscellaneous Fabricated Metal Products
351 Engines and Turbines
352 Farm and Garden Machine and Eqpt.
353 Construction
354 Metalworking Machinery
355 Special Industry Machinery
356 General Industry Machinery
357 Computer and Office Eqpt.
358 Refrigeration and Service Ind Machinery
359 Misc. Ind and Commercial Machinery
361 Electric Transmission and Distribution Eqpt.
362 Electrical Ind. Apparatus
363 Household Appliances
364 Electric Lighting and Wiring Eqpt.
365 Household Audio Video Eqpt.
366 Communications Eqpt.
365 Ophthalmic Goods
386 Photographic Equipment
387 Watches and Clockwork Devices
391 Jewelry Silverware Plated Ware
393 Musical Instruments
394 Toys Games Athletic Goods
395 Pens and Artists' Materials
396 Costume Jewelry not Pr. Metal
399 Misc Manufacturing Industries
382 Lab Apparatus etc.