

Price transmission within the Producer Price Index Final Demand–Intermediate Demand aggregation system

This article examines the causal direction of price change within the Producer Price Index Final Demand–Intermediate Demand aggregation system. The analysis provides evidence of forward price transmission in both the commodity-type and production-flow portions of the system.

In 2014, the Producer Price Index (PPI) program of the Bureau of Labor Statistics (BLS) transitioned from the Stage of Processing (SOP) system to the Final Demand–Intermediate Demand (FD–ID) system as the key structure used for analyzing the behavior of producer prices. The FD–ID system expanded PPI aggregate index coverage beyond that of the SOP system (which included only goods sold for personal consumption and as private capital investment) through the addition of indexes for services, construction, exports, and government purchases.

The FD–ID system comprises two main portions: final demand and intermediate demand. The final-demand portion of the system measures price change for goods, services, and construction products sold for personal consumption, as capital investment, for export, and to government. Final demand represents the last stage in the domestic chain of production, because final-demand products are sold to an end user and are not used as an input to another domestic product. Examples of final-demand products include automobiles sold to consumers, textile machinery sold as capital investment, legal services purchased by the government, healthcare services sold for personal consumption, and construction sold as capital investment. The intermediate-demand portion of the FD–ID system measures price change for goods, services, and construction products sold to businesses as inputs to production, excluding capital investment. Intermediate-demand products can be used as inputs to other intermediate-demand products or as inputs to final-demand products. Crude petroleum sold to refineries, car parts sold to automobile manufacturers, and business consulting services sold to accounting firms are examples of intermediate-demand products.



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In order to meet the needs of different data users, the FD–ID aggregation system includes two separate treatments of intermediate demand, each designed for a different analytical use. The first treatment organizes intermediate-demand products by type of product, establishing a “commodity-type model” of price change. The intermediate-demand indexes in this model provide value to data users by supplying specific information about the type(s) of products creating inflationary pressure in the economy. The second treatment organizes the same intermediate-demand commodities¹ into a production-flow model. The production-flow model assigns commodities to stages in such manner that the commodities included in each sequential stage are the inputs used to produce commodities in the next stage. This model is more suitable for analyzing price transmission within the U.S. economy than the commodity-type model, which provides a less technically sophisticated and more accessible view of intermediate-demand inflation.²

This article uses empirical techniques to examine the causal direction of price change within the FD–ID system. The relationships between the index for final demand and both the commodity-type and production-flow intermediate-demand indexes are examined separately. For the intermediate-demand-by-commodity-type portion of the system, an econometric model is estimated to examine the causal relationship between prices for different types of intermediate-demand products (unprocessed goods, processed goods, and services) and final-demand prices. For the production-flow portion of the system, a second econometric model is estimated to examine the causal relationship between prices at intermediate stages of production and final-demand prices. The analysis provides evidence of forward price transmission in both the commodity-type and production-flow models; however, the causal relationships are stronger and clearer in the production-flow model.

A number of authors have examined the causal relationships between prices at intermediate stages of production and final prices, but thus far no study has done so with the use of the FD–ID price-index system. S. Brock Blomberg and Ethan Harris investigated the connection between, on the one hand, the core Consumer Price Index (CPI) and, on the other hand, the Commodity Research Bureau spot index, the *Journal of Commerce* index of industrial materials’ prices, the PPI for crude goods, the National Association of Purchasing Managers price index, and the Federal Reserve of Philadelphia’s prices-paid index.³ Fred Furlong and Robert Ingenito analyzed the causal relationships between CPI inflation and the Commodity Research Bureau’s indexes for all commodities and raw materials.⁴ Todd Clark, using a vector autoregression (VAR) approach, built forecast models of the CPI to study the relationships between PPI SOP indexes and the CPI.⁵ Tae-Hwy Lee and Stuart Scott used vector error-correction models to examine price transmission within the PPI SOP system.⁶ Jonathan Weinhausen constructed impulse-response functions and variance decompositions from VAR models to study the connection between the PPIs for crude goods, intermediate goods, and finished goods and the CPI.⁷

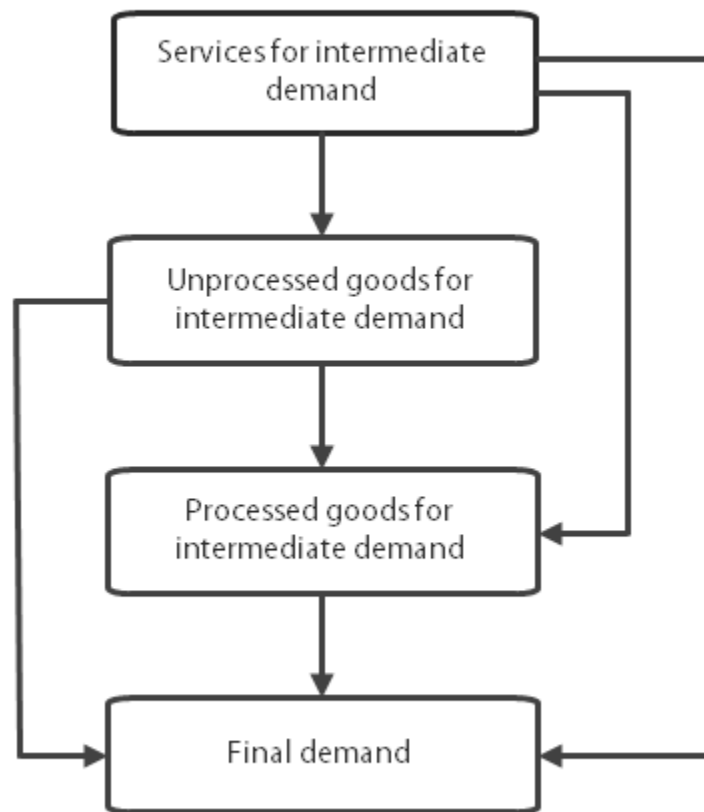
Price transmission within the commodity-type model

The intermediate-demand-by-commodity-type portion of the FD–ID system includes indexes for unprocessed goods for intermediate demand, processed goods for intermediate demand, and services for intermediate demand. The index for unprocessed goods for intermediate demand comprises prices for unfabricated goods purchased by businesses as inputs to production. Examples include crude petroleum sold to refineries, scrap metal sold to fabricated-metal producers, and wheat sold to flour manufacturers. The index for processed goods for intermediate demand includes prices for fabricated goods sold as business inputs. Car parts sold to automobile manufacturers, flour sold to bread producers, and diesel fuel sold to trucking companies are examples of goods included in this index. The index for services for intermediate demand comprises prices for business services. Examples include

legal services provided to manufacturers, engineering services provided to aircraft manufacturers, and accounting services provided to consulting firms.

Within the commodity-type model, all types of intermediate-demand products can be used as inputs to produce final-demand products, but only some types of intermediate-demand commodities are substantial inputs to one another. For example, both unprocessed and processed goods for intermediate demand are inputs to final-demand products, and although unprocessed goods for intermediate demand can be used as inputs to processed goods for intermediate demand, processed goods for intermediate demand are not significant inputs to unprocessed goods for intermediate demand. Figure 1 illustrates the economic chain of production within the commodity-type model. An arrow leading from one type of product to another indicates that the first product type can be used as an input to produce the second.

Figure 1. Economic production chain for the commodity-type model of intermediate demand



Source: U.S. Bureau of Labor Statistics.

Intermediate-demand services are found first in the production chain because they are likely inputs to all other types of products; by contrast, in most cases, other product types are not substantial inputs to intermediate-demand services. Unprocessed goods for intermediate demand are second, since they can be inputs to processed goods for intermediate or final demand, but neither processed goods for intermediate demand nor final-demand products are a significant source of inputs to unprocessed goods for intermediate demand. Processed goods for intermediate demand are third, because they are inputs to final-demand products, but not vice versa. The

economic production chain ends with final-demand products, which are, by definition, not inputs to any of the products included at earlier stages of the model.

A VAR model can be used to examine the nature of causal price-transmission relationships among the indexes for intermediate demand by commodity type and the indexes for final demand. VAR modeling involves estimating a system of equations in which each variable is expressed as a linear combination of lagged values of itself and all other variables in the system.⁸ A four-variable VAR was estimated from the PPIs for services for intermediate demand, unprocessed goods for intermediate demand, processed goods for intermediate demand, and final demand. The estimation used monthly data from October 2009 through December 2014. (FD–ID data series typically begin in October 2009.) All data were seasonally adjusted and converted to month-to-month percentage-growth form.

A time series is stationary if the mean, variance, and covariance of the series are not dependent on time. The estimation of a VAR with nonstationary data is problematic, because the tests used to estimate the significance of the VAR coefficients in such a procedure would not be valid. To test for stationarity, the Dickey–Fuller test was applied; in this one-tailed test, the null hypothesis is that the time series is not stationary. A large negative test statistic would reject the null hypothesis and imply that the time series is stationary.⁹ Dickey–Fuller tests performed on the indexes for final demand and intermediate demand by commodity type indicated that, when the data are converted to percentage-growth form, all of the time series are stationary. To determine the correct lag structure of the VAR, the Schwarz information criterion was implemented.¹⁰ The criterion suggested that a VAR whose equations have one lag is optimal; therefore, the VAR was estimated with the use of one lag of each variable.

The VAR model was first used to test for Granger causality among the indexes. A variable is said to Granger-cause a second variable when adding past values of the variable to an autoregressive model of the second variable improves the predictability of the latter. Wald statistics were used to test the null hypothesis of no Granger causality. Wald tests are based on measuring the extent to which the unrestricted estimates fail to satisfy the restrictions of the null hypothesis. A small p -value of the Wald statistic would reject the null hypothesis of no feedback to the dependent variable, and a large p -value of the Wald statistic would imply that the null hypothesis is not rejected. A p -value of less than 0.01 would reject the null hypothesis at the 99-percent confidence level, whereas a p -value of 0.05 or less would do so at the 95-percent confidence level. P -values greater than 0.05 would suggest acceptance of the null hypothesis of no Granger causality.¹¹

In addition to testing for Granger causality from individual indexes to the dependent variable, the analysis included Granger-causality tests of joint lagged values of all variables that would precede or follow the dependent variable in the economic production chain outlined in figure 1. For example, the null hypothesis that prices for services, unprocessed goods, and processed goods for intermediate demand do not jointly Granger-cause final-demand prices was tested. The results of the Granger-causality tests are presented in table 1.

Table 1. Granger-causality tests for commodity-type model

Null hypothesis	Chi-square	p -value
Dependent variable: Services for ID		
Unprocessed goods for ID = 0	0.205	0.651
Processed goods for ID = 0	1.491	.222

See footnotes at end of table.

Table 1. Granger-causality tests for commodity-type model

Null hypothesis	Chi-square	p-value
Final demand = 0	.258	.611
Unprocessed goods for ID, processed goods for ID, and final demand = 0	3.913	.271
Dependent variable: Unprocessed goods for ID		
Services for ID = 0	.056	.812
Processed goods for ID = 0	.748	.387
Final demand = 0	1.311	.252
Processed goods for ID and final demand = 0	1.315	.518
Dependent variable: Processed goods for ID		
Services for ID = 0	.012	.913
Unprocessed goods for ID = 0	5.273	.022 ⁽¹⁾
Services for ID and unprocessed goods for ID = 0	5.296	.071
Final demand = 0	.325	.569
Dependent variable: Final demand		
Services for ID = 0	.077	.782
Unprocessed goods for ID = 0	6.213	.013 ⁽¹⁾
Processed goods for ID = 0	5.496	.019 ⁽¹⁾
Services for ID, unprocessed goods for ID, and processed goods for ID = 0	20.477	.000 ⁽²⁾
Notes:		
⁽¹⁾ Significant at the 95-percent confidence level.		
⁽²⁾ Significant at the 99-percent confidence level.		
Note: ID = Intermediate demand.		
Source: Author's calculations based on data from the U.S. Bureau of Labor Statistics.		

The Granger-causality tests suggest that price changes for less processed intermediate-demand goods are passed forward to more processed intermediate-demand goods and to final demand, but that price changes for intermediate-demand services are not passed through to intermediate-demand goods or to final demand. The tests show that the index for unprocessed goods for intermediate demand Granger-causes both the index for processed goods for intermediate demand and the index for final demand. Moreover, prices for processed goods for intermediate demand Granger-cause final-demand prices, and prices for unprocessed goods for intermediate demand, processed goods for intermediate demand, and intermediate-demand services jointly Granger-cause final-demand prices. In no instance does the index for intermediate-demand services alone Granger-cause any other variables in the system. The tests also suggest that price changes for final demand do not lead to changes in intermediate-demand prices, as the final-demand index does not Granger-cause any intermediate-demand indexes included in the model.

VAR coefficients are difficult to interpret because of the multivariate nature of the models. Accordingly, impulse-response functions and variance decompositions were developed to assist in interpreting the VARs.¹² Impulse-response functions measure the effect of a one-standard-deviation perturbation of a variable in a system of equations on current and future values of all variables in the system. Variance decompositions show the percentage of forecast-error variance in one variable of the VAR that is explained by perturbations to all variables used in the VAR.¹³ Because shocks within a VAR are generally contemporaneously correlated, a random shock to one variable often occurs simultaneously with shocks to other variables. To overcome this problem, the residuals

may be orthogonalized by a Cholesky decomposition in which the covariance matrix of the residuals is lower triangular. In this decomposition, a shock to one variable in the system contemporaneously affects only variables ordered after that variable in the VAR, and the VAR is given a causal interpretation.¹⁴ To calculate the impulse-response functions and variance decompositions of variables in the commodity-type model, the residuals were orthogonalized by a Cholesky decomposition using the following ordering of commodities: services for intermediate demand, unprocessed goods for intermediate demand, processed goods for intermediate demand, final demand. This ordering was chosen because economic theory predicts that price changes for inputs costs would be passed forward to more processed products.

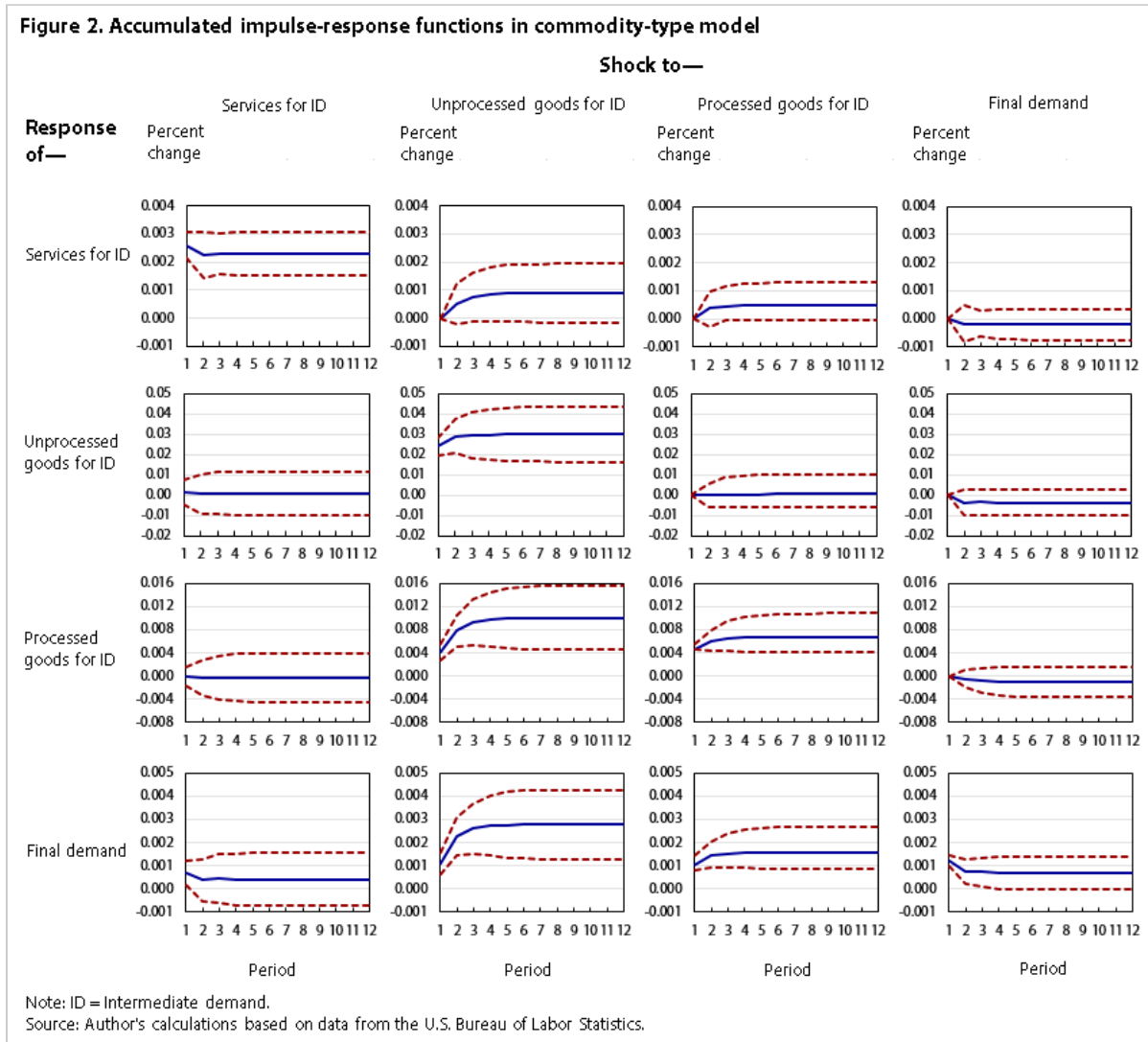


Figure 2 presents the accumulated impulse-response functions of one-standard-deviation shocks to the indexes for services for intermediate demand, unprocessed goods for intermediate demand, processed goods for intermediate demand, and final demand. To represent the statistical significance of the impulse-response functions, standard-error bands (dashed red lines) were constructed with the use of the software program EViews 5.0.¹⁵ The impulse responses are significant at the 95-percent confidence level when both standard-error bands are simultaneously above or below zero on the y-axis.

The accumulated impulse-response functions indicate that, within the commodity-type model, price changes for less processed goods are passed forward to more processed commodities. An unanticipated change to the index for unprocessed goods for intermediate demand significantly affects prices for both processed goods for intermediate demand and final demand. Likewise, a shock to the index for processed goods for intermediate demand leads to significant changes in the index for final demand. The impulse-response functions also provide modest support for the notion that changes in prices for intermediate-demand services are passed onto final-demand prices, because an unanticipated change in the index for services for intermediate demand leads to a marginally significant change in the final-demand index. The impulse-response functions do not indicate that changes in final-demand prices are transmitted to commodities found earlier in the production chain, or that prices for partially processed intermediate-demand goods are transmitted backward to prices for unprocessed goods. A shock to the index for final demand does not lead to significant changes to any other variables in the model, and unanticipated changes in the index for processed goods for intermediate demand do not lead to significant changes in the index for unprocessed goods for intermediate demand.

Table 2 presents the variance decompositions of the commodity-type indexes after 12 months.¹⁶ The variance decompositions reinforce the earlier finding that changes in final-demand prices are affected by price changes for intermediate-demand commodities. Unanticipated changes in prices for services for intermediate demand, unprocessed goods for intermediate demand, and processed goods for intermediate demand account for, respectively, about 9, 43, and 21 percent of the forecast-error variance in the index for final demand. The variance decompositions also indicate that changes in processed-goods prices can result from changes in unprocessed-goods prices, because shocks to unprocessed-goods prices account for approximately 58 of the forecast-error variance in the index for processed goods for intermediate demand. Finally, the variance decompositions show that very little of the forecast-error variance in either the indexes for services for intermediate demand or the indexes for unprocessed goods for intermediate demand can be attributed to other variables in the model.

Table 2. Variance decompositions after 12 months, commodity-type model

Decomposition variable	Percentage of forecast errors due to—			
	Services for ID	Unprocessed goods for ID	Processed goods for ID	Final demand
Services for ID	93.14	4.51	1.95	0.40
Unprocessed goods for ID	.48	97.48	.02	2.02
Processed goods for ID	.09	57.96	41.34	.60
Final demand	8.77	43.40	20.55	27.29

Note: ID = Intermediate demand.

Source: Author's calculations based on data from the U.S. Bureau of Labor Statistics.

Price transmission in the production-flow model

The production-flow model of intermediate demand is a stage-based system of price indexes. It is constructed in a manner that maximizes forward flow of production between stages, while minimizing backward flow of production. It contains four main indexes: intermediate-demand stage 1, intermediate-demand stage 2, intermediate-demand stage 3, and intermediate-demand stage 4. Final demand can be added as the final stage in the model.

Indexes for the four intermediate-demand stages were developed by first assigning each industry in the economy to a stage. Industries assigned to the fourth stage produce output primarily consumed as final demand, industries in the third stage produce output primarily consumed by stage-4 industries, industries assigned to the second stage produce output primarily consumed by stage-3 industries, and industries assigned to the first stage produce output primarily consumed by stage-2 industries. Production-flow indexes track prices for the net inputs consumed by industries in each of the four stages of production. For example, the stage-4 intermediate-demand index tracks price changes for inputs consumed, but not produced, by industries included in the fourth stage of production. Hence, the stage-4 index measures price change in the inputs to production of industries that primarily produce final-demand commodities. The main sources of data used to develop these indexes were the Bureau of Economic Analysis “Use of commodities by industries, before redefinition” and “Make of commodities by industries, before redefinition” tables.¹⁷

In order to examine the nature of causal price-transmission relationships among the intermediate-demand-by-production-flow indexes and the final-demand indexes, a four-variable VAR was estimated with the use of monthly data from October 2009 through December 2014. The estimation included PPIs for stage-2 intermediate demand, stage-3 intermediate demand, stage-4 intermediate demand, and final demand. The stage-1 intermediate-demand index was omitted from the model because the transactions included at this stage are, by construction, backflow from earlier stages in the system, making stage 1 less useful for price-transmission analysis. All indexes were seasonally adjusted and converted to month-to-month percentage-growth form. Dickey-Fuller tests indicated that, when the data are converted to percentage growth form, all of the time series involved are stationary. To determine the correct lag structure of the VAR, the Schwarz information criterion was implemented. Again, the criterion suggested that a VAR whose equations have one lag is optimal; therefore, one lag of each variable was used to estimate the VAR.

Granger-causality tests were performed with the use of the VAR model. In addition to testing for Granger causality from individual indexes to the dependent variable, the analysis tested joint lagged values of all variables at stages of processing before and after the stage of the dependent variable. For example, the null hypothesis that prices for stage-2 and stage-3 intermediate demand do not jointly Granger-cause stage-4 intermediate demand was tested. Table 3 presents the results of the Granger-causality tests for the production-flow model.

Table 3. Granger-causality tests for production-flow model

Null hypothesis	Chi-square	p-value
Dependent variable: Stage-2 ID		
Stage-3 ID = 0	3.279	0.070
Stage-4 ID = 0	.543	.461
Final demand = 0	.034	.853
Stage-3 ID, stage-4 ID, and final demand = 0	3.667	.300
Dependent variable: Stage-3 ID		
Stage-2 ID = 0	4.001	.046 ⁽¹⁾
Stage-4 ID = 0	.635	.426
Final demand = 0	1.339	.247
Stage-4 ID and final demand = 0	1.363	.506
Dependent variable: Stage-4 ID		

See footnotes at end of table.

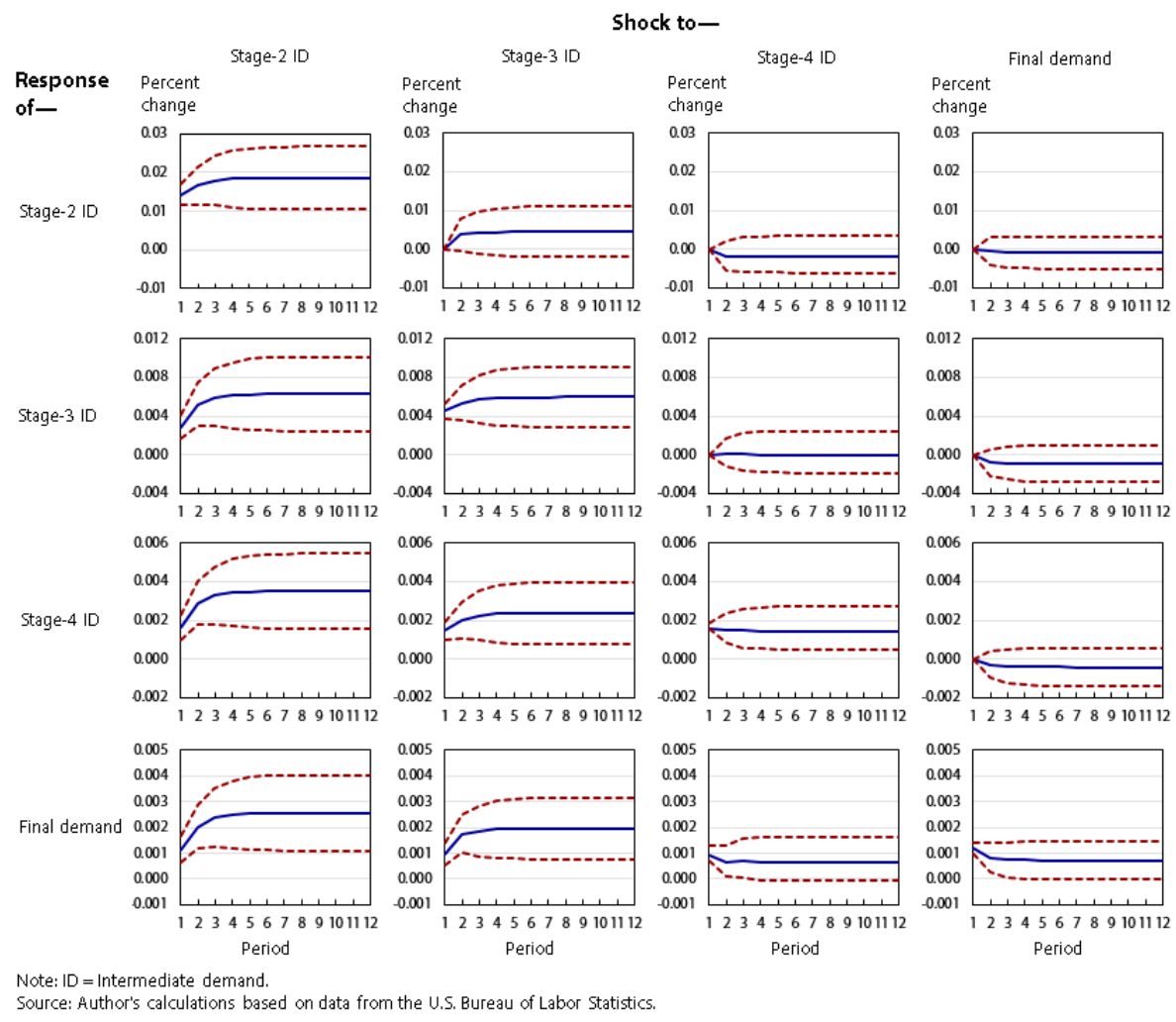
Table 3. Granger-causality tests for production-flow model

Null hypothesis	Chi-square	p-value
Stage-2 ID = 0	4.523	.033 ⁽¹⁾
Stage-3 ID = 0	.986	.321
Stage-2 ID and stage-3 ID = 0	5.851	.054
Final demand = 0	.803	.370
Dependent variable: Final demand		
Stage-2 ID = 0	2.220	.136
Stage-3 ID = 0	5.004	.025 ⁽¹⁾
Stage-4 ID = 0	.005	.943
Stage-2 ID, stage-3 ID, and stage-4 ID = 0	13.623	.004 ⁽²⁾
Notes:		
⁽¹⁾ Significant at the 95-percent confidence level.		
⁽²⁾ Significant at the 99-percent confidence level.		
Note: ID = Intermediate demand.		
Source: Author's calculations based on data from the U.S. Bureau of Labor Statistics.		

The Granger-causality tests show that price changes at each stage of production are explained by changes in prices at earlier stages of production, and not explained by prices at later stages of production. In no equation is an explanatory variable (or a combination of explanatory variables) significant if its stage of production follows that of the dependent variable. By contrast, the stage-2 intermediate-demand index Granger-causes the indexes for both stage-3 intermediate demand and stage-4 intermediate demand. Moreover, the stage-3 intermediate-demand index Granger-causes the final-demand index, and the indexes for intermediate demand at stages 2, 3, and 4 jointly Granger-cause the index for final demand.

As in the previous model, impulse-response functions and variance decompositions were constructed from an orthogonalized set of residuals. This was done with the use of a Cholesky decomposition based on the following ordering: stage-2 intermediate demand, stage-3 intermediate demand, stage-4 intermediate demand, final demand. This ordering was chosen because economic theory predicts that input price changes would be passed on to higher-level producers in the production chain. In addition, the Granger-causality tests suggest that this ordering is correct. The accumulated impulse-response functions are presented in figure 3.

Figure 3. Accumulated impulse-response functions in production-flow model



The accumulated impulse-response functions indicate that price changes within the production-flow model are passed forward through the stages of production. In every instance, an unanticipated price change at an earlier stage of the model results in significant price changes at later stages. For example, a shock to the index for stage-2 intermediate demand results in significant movements in the indexes for stage-3 intermediate demand, stage-4 intermediate demand, and final demand. Likewise, an unanticipated change in prices for stage-3 intermediate demand leads to significant changes in prices for stage-4 intermediate demand and for final demand. The impulse-response functions also imply that price movements are not passed backward through the stages of processing. In no instance does a price shock at a later stage of production lead to significant price movements at earlier stages.

Variance decompositions also suggest that price changes are passed forward, as opposed to backward, through the stages of the production-flow model. Table 4 shows that approximately 35, 25, and 15 percent of the forecast-error variance in the index for final demand are attributable to unanticipated changes in the indexes for stage-2 intermediate demand, stage-3 intermediate demand, and stage-4 intermediate demand, respectively. Unanticipated changes in the indexes for stage-2 intermediate demand and stage-3 intermediate demand account for 47 and 27 percent, respectively, of the forecast-error variance in the stage-4 intermediate-demand index, whereas shocks to final-demand prices account for only 1 percent of the forecast-error variance. Approximately 40

percent of the forecast-error variance in the stage-3 intermediate-demand index is explained by unexpected changes in the index for stage-2 intermediate demand, whereas innovations to prices for stage-4 intermediate demand and final demand explain very little of the forecast-error variance in the stage-3 intermediate-demand index. Finally, more than 90 percent of the forecast-error variance in the stage-2 intermediate-demand index can be attributed to unexpected changes in that index itself.

Table 4. Variance decompositions after 12 months, production-flow model

Decomposition variable	Percentage of forecast errors due to—			
	Stage-2 ID	Stage-3 ID	Stage-4 ID	Final demand
Stage-2 ID	91.72	6.22	1.88	0.18
Stage-3 ID	39.51	58.68	.07	1.73
Stage-4 ID	46.70	26.69	25.56	1.05
Final demand	35.19	24.64	14.62	25.55

Note: ID = Intermediate demand.

Source: Author's calculations based on data from the U.S. Bureau of Labor Statistics.

Conclusion

This article presented an empirical investigation of the nature of causal price relationships within the new PPI FD–ID system. Using two separate VAR models, the analysis examined causal relationships between the index for final demand and indexes for two PPI treatments of intermediate demand: commodity type and production flow.

The first VAR model was used to examine price transmission among the intermediate-demand-by-commodity-type indexes and the index for final demand. Impulse-response functions developed from the VAR model's coefficients indicated that price changes for less processed goods are passed forward to more processed commodities. The impulse-response functions also provided modest support for the notion that changes in prices for intermediate-demand services are passed onto other types of commodities. The impulse-response functions did not indicate that changes in final-demand prices are transmitted to commodities found earlier in the production chain, or that prices for partially processed intermediate-demand goods are transmitted backward to prices for unprocessed goods. Variance decompositions told a similar story. Substantial portions of the forecast-error variance in the index for final demand were explained by unanticipated changes in the indexes for all types of intermediate-demand commodities: unprocessed goods, processed goods, and services. Likewise, a large portion of the forecast-error variance in the index for processed goods for intermediate demand was accounted for by innovations in the index for unprocessed goods for intermediate demand.

The second VAR model was used to analyze the causal price relationships between the intermediate-demand-by-production-flow indexes and the index for final demand. Impulse-response functions from the VAR indicated that price changes are transmitted forward, but not backward, through the production-flow stages. In every instance, an unanticipated price shock resulted in a statistically significant change in prices at stages ahead of where the shock occurred. By contrast, in no case did a price shock lead to a significant change in prices at an earlier stage of the production-flow model. Variance decompositions also showed that price changes are passed forward, but not

backward, through the stages of the model. A substantial portion of the forecast-error variance at every stage was accounted for by unanticipated changes in prices at earlier stages, but not later stages.

Although the VAR models constructed from both the commodity-type and production-flow indexes indicated forward price transmission, the causal relationships were clearer and stronger in the production-flow model. Within that model, shocks to prices at earlier stages always produced significant changes to prices at later stages, and price changes were never significantly transmitted backward through the stages. Within the commodity-type model, price changes were transmitted forward to more processed commodities in most, but not all, cases. The clearer price transmission seen in the production-flow model is somewhat expected, because that model was constructed with the explicit goal of maximizing forward flow of production between stages while minimizing backward flow.

Overall, the results of this article confirm that the commodity-type and production-flow models of intermediate demand are measuring price transmission as they were intended to do when they were first conceptualized and constructed by BLS.

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NOTES

¹ The PPI definition of commodities includes goods, services, and construction products.

² For a detailed description of the PPI FD–ID system, see Jonathan C. Weinhaven, "A new, experimental system of indexes from the PPI program," *Monthly Labor Review*, February 2011, pp. 3–24, <https://www.bls.gov/opub/mlr/2011/02/art1full.pdf>.

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[12](#) Christopher A. Sims, "Macroeconomics and reality," *Econometrica*, January 1980, pp.1–48.

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[16](#) Walter Enders, *Applied econometric time series* (Hoboken, NJ: John Wiley & Sons, Inc., 2004), pp. 278–280.

[17](#) BEA input–output accounts data can be found at https://www.bea.gov/industry/io_annual.htm.

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Introducing 2012 fixed employment weights for the Employment Cost Index

Beginning with the release of December 2013 estimates, the ECI was reweighted to reflect 2012 employment counts. This reweighting accounted for updates to the occupational and industry classification systems, incorporating the 2010 Standard Occupational Classification system and the 2012 North American Industry Classification System. These changes had minimal impact on the historical continuity of the ECI.

The Employment Cost Index (ECI) is a quarterly economic data series that measures changes in the costs of employing a fixed set of labor inputs in the U.S. economy.¹ It is a fixed-employment-weighted Laspeyres index that, like most Laspeyres indexes, has fixed weights that are updated periodically.² With the release of December 2013 estimates, the ECI introduced 2012 fixed-employment weights to replace the 2002 fixed-employment weights that were in use from March 2006 through September 2013.³ The new weights are based on data from the U.S. Bureau of Labor Statistics (BLS) Occupational Employment Statistics (OES) survey, along with data from the Quarterly Census of Employment and Wages (QCEW) program.⁴

In addition to the new fixed-employment weights, BLS also changed the occupational and industry classification systems for the ECI. It now classifies occupations and industries with the 2010 Standard Occupational Classification (SOC) system and the 2012 North American Industry Classification System (NAICS), respectively. Because there are so few SOC and NAICS changes for the ECI at the publication level, switching to the new classification systems has had little impact on the historical continuity between the old indexes and the new.

This article examines the reweighting of the ECI and discusses its effects. Additionally, the article discusses the impact of reweighting on the seasonally adjusted ECI series and changes in seasonal adjustment methodology.



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The article concludes with a discussion of cost estimates from the Employer Costs for Employee Compensation (ECEC) data.

Background

For the ECI, BLS uses a probability-proportional-to-size (PPS) sampling procedure to select establishments from a sample frame, then assigns a 6-digit NAICS code to each establishment. For each sampled establishment, BLS field economists use an additional sampling procedure that ensures a random sample of jobs. Once the jobs are selected, they are matched to occupations, as defined by the SOC system. At the initial contact with the establishment, the field economists collect wage and benefit data pertaining to the selected jobs and subsequently update the data each quarter.

Weights are used to derive population estimates from the survey sample. With regard to the ECI, employment cost data from the sample are multiplied by the appropriate weights to obtain unbiased estimates for U.S. civilian, state and local government, and private-industry workers.⁵ Two sets of weights are used in the ECI: sample weights and fixed-employment weights.

Sample weights. Sample weights, also referred to as establishment–occupation weights, are assigned to each surveyed occupation within each establishment in the ECI sample. They reflect the inverse probability of selection of the establishment from the sample frame of all establishments within the scope of the ECI. Further, they reflect the inverse probability of selection of each occupation within the establishment. The sample weights are used to calculate current- and previous-quarter average hourly compensation costs for occupational groups within industry categories in private industry and state and local governments.

Fixed weights in the ECI. Fixed weights in the ECI are employment counts that remain the same over time until the next reweighting. A fixed employment weight applies to the broad occupational category within an industry category that the specific jobs represent. For example, in a particular industry, data might be collected from 20 establishments. In each establishment, a set of occupations will be selected randomly with a probability proportionate to the occupation’s employment in the establishment. In one establishment, the field economist might select industrial engineers, secretaries, and janitors. In another establishment in the same industry, the field economist might select architects, order clerks, and cooks. When BLS economists in the Office of Compensation and Working Conditions (OCWC) assign these occupations to the 2010 SOC categories of the ECI, they classify engineers and architects into the professional and related occupations category, secretaries and order clerks into the office and administrative support occupations category, and janitors and cooks into the service occupations category.

Occupational groups within industry categories are known as estimation cells, or cells for short. There are nine occupational groups (including management, business, and financial occupations; sales and related occupations; and service occupations) defined for each industry in both private industry and state and local governments. While the occupational groups for private industry and state and local governments are the same, the industry categories are different.

There are 58 industry categories defined for private industry (including construction, and food services and drinking places) and 13 industry categories defined for state and local governments (including health care and social assistance, and colleges, universities, and professional schools). Private industry sample jobs are sorted

into 522 estimation cells (9 major occupational groups sorted across 58 industries) while state and local government sample jobs are sorted into 234 estimation cells (9 major occupation groups sorted across 13 industries).

Classification systems. Beginning with the release of the March 2006 ECI, industries were classified by the NAICS 2002 and occupation groups were classified by the SOC 2000 system. With the release of December 2007 ECI data, industries were classified by the NAICS 2007. This continued until the December 2013 release, when the industry and occupational classifications were updated once again, to the NAICS 2012 and the SOC 2010, respectively.⁶

These changes to the classification systems have affected ECI estimates to varying degrees. The 2010 edition of the SOC had changes that necessitated reclassification of some occupations to a different occupational category.⁷ The change that had the most potential to impact the ECI, because of the number of workers affected, was the reclassification of flight attendants from service occupations to transportation and material moving occupations. However, because the overlap between 2000 SOC and 2010 SOC for these occupations is greater than 98 percent, this change had a negligible impact on the service occupations and transportation and material moving series.

The update from the 2002 NAICS to the 2007 NAICS, and the subsequent update from the 2007 NAICS to the 2012 NAICS, had minimal impact on the ECI estimates.

Reasons for reweighting

ECI measures are used in three main types of analysis:

- Measurement of the total change in labor cost over the time period for which the indexes are available
- Comparisons of changes in labor costs over different subperiods (for example, comparison of the change between September 2013 and September 2014 with that between September 2010 and September 2011)
- Measurement of the current rate of change in labor costs

No single index can be ideal for all three types of analysis. For instance, an index that is appropriate for analyzing long-run changes will not be the best for measuring the current rate of labor cost increases, and vice versa.

If the ECI were used only to measure the long-run change in labor costs of a fixed set of labor inputs, the employment weights would seldom need to be updated. Similarly, the value of the ECI in comparing changes in labor costs over different subperiods depends on holding the weights fixed for extended periods. The unchanging weights are necessary, in these cases, to ensure that the same set of labor inputs are compared over time.

In contrast, if the ECI is used to measure the recent rate of labor cost increases, then weights should be as current as possible. With current weights, the index of labor costs would measure the change between, for example, September 2012 and December 2012 in the cost of purchasing the set of labor inputs employed in September 2012. An index with current weights differs from the existing ECI Laspeyres index, which would estimate current labor cost increases as the change between September 2012 and December 2012 in the cost of purchasing the set of labor inputs employed at the reference point of the 2002 Occupational Employment Statistics (OES) survey (the source of the fixed employment weights used to derive ECI estimates from 2006 through September 2013). In

general, the accuracy of a Laspeyres index varies inversely with the magnitude of shifts in employment among industries and occupations.

If the ECI's employment weights were changed every quarter to improve the measurement of current rates of labor cost increases, it would be possible to derive a type of Laspeyres index by multiplying together quarter-to-quarter changes (expressed as ratios). Such a "chain" index would provide a better estimate of the rate of labor cost increase for each quarter than the current ECI, which does not change employment weights every quarter. The chain index would not, however, provide the change in the cost of a fixed set of workers for periods longer than one quarter, and changes for different subperiods would not be for the same set of labor inputs.

The ECI is a compromise between a pure Laspeyres index, which would hold employment weights fixed permanently, and an index that uses new weights each quarter; that is, the ECI's weights are changed periodically after remaining fixed for a number of years. Because the ECI's employment weights remain fixed for long periods, the index could lose its value as a measure of current change.

A number of ECI studies have indicated that the period-to-period change in a fixed-weight Laspeyres index is relatively insensitive to the weights used when the weights vary within the range common to many economic variables. Thus, the quarter-to-quarter changes calculated with a Laspeyres index are apt to be quite close to the quarter-to-quarter changes obtained by using the previous quarter's employment weights.⁸ For this reason, the ECI has employed one set of weights for a number of years. This approach preserves the analytical value of the Laspeyres index as a measure of change in labor costs both different subperiods and over the long run.

As the weights become older, however, it becomes increasingly likely that current rates of change using the fixed weights could differ from those based on more recent weights by an amount great enough to be important in economic analysis.⁹ To ensure that the ECI will continue to provide a good approximation of the current rate of labor cost increase, more recent weights were introduced. In addition, changes to industry and occupation classification systems, such as the mandated changes to the NAICS and SOC systems, made it necessary to reweight the ECI. Without such changes, the ECI would be less relevant to the economy and less useful when relating to other statistical measures that have transitioned to the new systems.

Consequences of reweighting

The new weights alter what the ECI is measuring when comparisons are made between estimates based on different sets of employment weights. That is, any change calculated by dividing an ECI index number based on new weights by an index number using earlier weights is not in the strictest sense a Laspeyres index estimate. Reweighting improves the currency of the index, but has the potential to disrupt historical continuity.

For example, between any two periods from December 2005 to September 2013, when 2002 weights were used, the relative difference in the index would be the change in the cost of employing the 2002 workforce. Between any two periods after September 2013, the relative difference would be the change in the cost of employing the 2012 workforce. However, the ratio of an index for a period after September 2013 to one for a period before September 2013 cannot be interpreted in terms of the cost of employing any fixed workforce; that is, the ratio is not a true Laspeyres index number.

Subindexes. The impact of reweighting on each ECI subindex, considered separately, is the same as that on the aggregate index. The reweighting causes the change in cost for the subindex to be closer to the change in current cost, but it can also result in a disruption of the subindex as a measure of long-run change and of change between periods before and periods after the new weights are introduced. An additional issue is raised, however, when the reweighted subindexes are introduced. This issue concerns the relationship between the change in the aggregate index and the changes in the component subindexes.

The aggregate Laspeyres index can be expressed as a weighted sum of any set of exhaustive and mutually exclusive Laspeyres subindexes where the weights sum to one.¹⁰ This is a very desirable property for two reasons. First, it guarantees that the change in the aggregate index falls within the range of changes in the subindex; the change in the aggregate index cannot be greater than the largest change among the subindexes or less than the smallest (except when rounding). Second, the property also makes it possible to assign the change in the aggregate index to the subindex; that is, one can determine how much of the change in the aggregate is attributable to the change in each subindex.

For comparisons spanning the date on which the new weights were introduced, the aggregate Laspeyres index cannot be expressed as the weighted sum of any set of exhaustive and mutually exclusive subindexes. Accordingly, the change in the aggregate index between March 2013 and March 2014 might be larger or smaller than the change in any of the subindexes.

Sources of new weights

The primary source of the new weights is the BLS OES survey, supplemented by data from the QCEW program.¹¹ The OES survey is a semiannual mail survey of 1.2 million nonfarm establishments over a 3-year cycle. The survey collects occupational employment data by industry and area. BLS produces the OES survey materials and selects the establishments to be surveyed. State Workforce Agencies mail the survey materials to the selected establishments and make follow-up calls to request data from nonrespondents or to clarify data.

Most cells used OES employment counts directly. However, for some state and local government cells (excluding hospitals, educational services, and public administration), employment counts are not available for individual industries because those industries have relatively small employment figures. For these industries, the OES provided total employment by occupational group for state and local governments separately using data imputed from the QCEW.

The imputation for missing industry detail was done by, first, apportioning total OES employment in the combined industries among the component industries using data from the QCEW, and second, apportioning total employment for each industry among the occupational groups by assuming the same occupational distribution in each of the industries as that of state and local governments separately.

Table 1 compares percent distribution by private industry and occupation of the 2002 and 2012 weights. Among occupations, there has been a shift toward management, business and financial occupations; professional and related occupations; and service occupations. Among industries, there has been a shift toward educational services, health services, and leisure and hospitality.

Table 1: Percent distribution of employment within the scope of the Employment Cost Index, private industry

Occupational and industry group	2002	2012
All workers	100.0	100.0
Occupational group		
Management, business, and financial	9.3	9.8
Professional and related	14.0	16.4
Sales and related	12.5	12.7
Office and administrative support	17.9	16.6
Construction, extraction, farm, fishing, and forestry	5.3	4.3
Installation, maintenance, and repair	4.4	4.2
Production	10.1	7.7
Transportation and material moving	8.1	7.4
Service	18.3	20.9
Industry group		
Goods-producing industries	21.1	16.8
Mining	.5	.7
Construction	6.3	5.2
Manufacturing	14.4	10.9
Service-providing industries	78.9	83.2
Utilities	.6	.5
Transportation and warehousing	4.0	4.0
Wholesale trade	5.3	5.2
Retail trade	14.3	13.8
Information	3.1	2.5
Financial Activities	7.2	6.9
Professional and business services	15.0	16.4
Educational services	1.8	2.5
Health services	12.6	15.4
Leisure and hospitality	11.3	12.5
Other services	3.5	3.5

Source: U.S. Bureau of Labor Statistics, Occupational Employment Survey.

Testing the effects of the new weights

To evaluate the impact of using 2012 weights in place of 2002 weights, BLS researchers conducted a test that estimated the rates of change for 2005–13 using the 2012 weights. Researchers then compared the results with the published estimates based on 2002 weights. The test results, presented in table 2 show that, for the group with the highest level of aggregation—civilian workers—rates of change in compensation costs for 2005–13 vary only slightly when 2012 weights rather than 2002 weights are used. For example, on the basis of 2012 weights, the estimated change in compensation costs over the 7½-year period ending June 2013, 18.9 percent (the cumulative index change at that date), is essentially the same as the change obtained with 2002 weights, 19.0 percent. The 3-month changes never differed by more than one-tenth of a percentage point over the entire March 2006–June 2013 period.

Table 2. Indexes and percent changes in total compensation costs by weight periodicity, civilian workers, December 2005–June 2013⁽¹⁾

Reference year and quarter	2002 weights			2012 weights		
	Index	3-month percent change	12-month percent change	Index	3-month percent change	12-month percent change
2005-Q4	100.0	0.5	3.2	100.0	0.5	3.1
2006-Q1	100.7	.7	2.8	100.7	.7	2.7
2006-Q2	101.6	.9	3.0	101.5	.8	2.9
2006-Q3	102.7	1.1	3.3	102.7	1.2	3.2
2006-Q4	103.3	.6	3.3	103.4	.7	3.4
2007-Q1	104.2	.9	3.5	104.2	.8	3.5
2007-Q2	105.0	.8	3.3	105.0	.8	3.4
2007-Q3	106.1	1.0	3.3	106.1	1.0	3.3
2007-Q4	106.7	.6	3.3	106.8	.7	3.3
2008-Q1	107.6	.8	3.3	107.6	.7	3.3
2008-Q2	108.3	.7	3.1	108.4	.7	3.2
2008-Q3	109.2	.8	2.9	109.2	.7	2.9
2008-Q4	109.5	.3	2.6	109.5	.3	2.5
2009-Q1	109.9	.4	2.1	110.0	.5	2.2
2009-Q2	110.2	.3	1.8	110.3	.3	1.8
2009-Q3	110.8	.5	1.5	110.8	.5	1.5
2009-Q4	111.0	.2	1.4	111.0	.2	1.4
2010-Q1	111.8	.7	1.7	111.8	.7	1.6
2010-Q2	112.3	.4	1.9	112.2	.4	1.7
2010-Q3	112.9	.5	1.9	112.9	.6	1.9
2010-Q4	113.2	.3	2.0	113.2	.3	2.0
2011-Q1	114.0	.7	2.0	113.9	.6	1.9
2011-Q2	114.8	.7	2.2	114.6	.6	2.1
2011-Q3	115.2	.3	2.0	115.1	.4	1.9
2011-Q4	115.5	.3	2.0	115.4	.3	1.9
2012-Q1	116.2	.6	1.9	116.2	.7	2.0
2012-Q2	116.8	.5	1.7	116.8	.5	1.9
2012-Q3	117.4	.5	1.9	117.3	.4	1.9
2012-Q4	117.7	.3	1.9	117.6	.3	1.9
2013-Q1	118.4	.6	1.9	118.3	.6	1.8
2013-Q2	119.0	.5	1.9	118.9	.5	1.8

Notes:

⁽¹⁾ Most of the estimates in this table are classified by the North American Industry Classification System (NAICS) and the Standard Occupational Classification (SOC) system. The 2002-weighted 3-month percent change for 2005-Q4 and the 2002-weighted 12-month percent changes for 2005-Q4 through 2006-Q3 are based on data classified by the Standard Industrial Classification system and the Occupational Classification System Manual.

Source: U.S. Bureau of Labor Statistics, National Compensation Survey.

Table 3 shows that the effects of the weight change are more substantial below the most aggregate level than at the aggregate level. The largest difference in indexes is 1.2 index points for the information industry, but expressed as an average annual rate of change (over the 7½ years since the base period of the index, December 2005), the difference was only 0.1 percentage point per year.

Table 3. Total compensation cost indexes and percent changes for economic sectors and selected occupational and industry groups, June 2013 (December 2005=100)

Category	Index		Average annual percent change ⁽¹⁾	
	2002 weights	2012 weights	2002 weights	2012 weights
Civilian workers	119.0	118.9	2.3	2.3
State and local government	120.7	120.8	2.5	2.6
Private industry	118.6	118.5	2.3	2.3
Occupational group				
Management, business, and financial	119.3	119.1	2.4	2.4
Professional and related	119.5	119.6	2.4	2.4
Sales and related	114.5	113.7	1.8	1.7
Office and administrative support	120.4	120.1	2.5	2.5
Construction, extraction, farming, fishing, and forestry	118.9	119.3	2.3	2.4
Installation, maintenance, and repair	119.3	119.2	2.4	2.4
Production	116.1	116.6	2.0	2.1
Transportation and material moving	118.6	119.1	2.3	2.4
Service occupations	118.3	117.6	2.3	2.2
Industry group				
Goods-producing	117.0	117.1	2.1	2.1
Construction	117.6	117.4	2.2	2.2
Manufacturing	116.3	116.1	2.0	2.0
Service-providing	119.1	118.8	2.4	2.3
Utilities	127.4	127.3	3.3	3.3
Transportation and warehousing	119.7	119.0	2.4	2.3
Wholesale trade	116.8	116.3	2.1	2.0
Retail trade	117.4	117.2	2.2	2.1
Information	118.6	117.4	2.3	2.2
Financial activities	118.0	117.1	2.2	2.1
Professional and business services	120.7	120.5	2.5	2.5
Educational services	119.9	119.7	2.4	2.4
Health services	119.9	119.8	2.4	2.4
Leisure and hospitality	116.9	116.7	2.1	2.1
Other services, except public administration	119.8	119.9	2.4	2.4

Notes:

⁽¹⁾ The average annual percent change here is the geometric mean percent change over 7 ½ years, from December 2005 (the base period of the index) to June 2013.

Source: U.S. Bureau of Labor Statistics, National Compensation Survey.

Effects of reweighting on seasonal adjustment

ECI series that have a seasonal pattern are seasonally adjusted, either directly or indirectly. Direct seasonal adjustments are calculated by dividing the index by the seasonal factor for the series. Indirect seasonal adjustments are calculated for aggregate series by taking a weighted sum of seasonally adjusted component indexes. The aggregation weights reflect the relative importance of each series in the base period. The use of indirect seasonal adjustment provides consistency between the seasonally adjusted aggregate and its adjusted-

directly components.¹² Seasonal factors are revised annually and historical seasonally adjusted indexes and 3-month percent changes are revised for 5 years, after which the estimates are final.¹³

In general, the choice of whether to use direct or indirect seasonal adjustment is related to the level of index aggregation. For series that are directly adjusted, the adjustment generally occurs at relatively low levels of aggregation, such as retail wages and salaries. An example of a series that is seasonally adjusted by the indirect method is civilian total compensation, for which there are 43 wages and salaries industry components and 43 total benefits cost industry components. All total compensation series are seasonally adjusted indirectly. Indexes for wages and salaries and total benefits for all aggregate industry and occupation groups (such as the trade, transportation, and utilities wages and salaries index and the management, professional, and related occupations indexes) are indirectly adjusted as well.¹⁴

Direct seasonal adjustment for December 2013. For the December 2013 direct seasonal adjustment of reweighted indexes, the seasonal factors are those estimated for the 2013 seasonal adjustment revision. These factors were derived from existing index values through December 2012 and based on the 2002 fixed employment weights. The use of these seasonal factors to adjust indexes for December 2013 is consistent with the analysis of the not-seasonally-adjusted series, which found relatively small differences between the 2002-weighted and 2012-weighted estimates for most series.

Indirect seasonal adjustment and linking December 2013 indexes to September 2013 indexes. For indexes with indirect seasonal adjustments, the introduction of the 2012 employment weights requires a change in the aggregation weight of each component series to reflect its relative importance in terms of employment in 2012 rather than in 2002. The absolute differences in aggregation weights based on the 2002 fixed employment weights and those based on the 2012 fixed employment weights range from near zero to 10.6 percentage points. The largest increase in component aggregation weights is for state and local government hospitals wages and salaries. The largest decrease in aggregation weight among published series is 5.4 percentage points for private industry production occupations wages and salaries.

Because the aggregation weights used for December 2013 are based on 2012 fixed employment weights and the aggregation weights for September 2013 (and previous quarters) are based on the 2002 fixed employment weights, an adjustment to the December 2013 seasonally adjusted indexes was necessary to maintain continuity between the two sets of aggregation weights. Without an adjustment, the observed changes between September and December 2013 would have reflected both the cost-change effect (the economic change) and the weight-change effect (the change due to using a different set of employment weights).

In order to remove the weight-change effect, researchers applied aggregation weight adjustment factors to the December 2013 seasonally adjusted indexes that were derived indirectly. For the period of the reweighting, the adjustment factors represent an adjustment to the December 2013 level of the index for the indirect seasonally adjusted series based on the difference in the aggregation of the September 2013 component indexes under the old weights versus the new weights. Therefore, the adjustment factor must also be applied to all subsequent quarters to ensure that the 3-month percent change in the index never reflects the weight-change effect. A detailed description of the aggregation weight adjustment procedure is presented in the Appendix.

Seasonal adjustment revision. Beginning with the March 2014 revision, to include the reweighted indexes, the 10-year data span of not seasonally adjusted indexes used to estimate revised seasonal factors consists of a joined series of 2002 fixed-employment-weighted indexes for September 2013 and earlier years and 2012 fixed employment-weighted indexes for December 2013. Since most of the data span currently consists of 2002 fixed employment-weighted indexes, the inclusion of reweighted indexes is not expected to have a substantial effect on the revised seasonal factors. But over time, as more reweighted indexes are included in the data span, the seasonal factors will reflect proportionally more of the 2012 reweighting. There is no change in the procedures for the 5-year revision of historical indexes and 3-month percent changes. The most recent revisions were introduced with the March 2016 ECI release.

Impact of SOC changes on the Employer Costs for Employee Compensation

The Employer Costs for Employee Compensation (ECEC) is a product of the National Compensation Survey which was developed from wage and benefit data that was collected for the ECI program. The ECEC measures employer costs for wages, salaries and employee benefits for nonfarm private, state government, and federal government workers. ECEC estimates are based on current employment weights, so reweighting the ECI has no effect on those estimates. However, beginning with the fourth quarter of 2013, estimates from the ECEC were affected by SOC changes. One change in 2010 SOC that affected both the ECI and the ECEC was the reclassification of flight attendants from service occupations to transportation and material moving occupations. A second change defined registered nurses more narrowly by removing nurse anesthetists, nurse midwives, and nurse practitioners from this category. This affected the ECEC, and not the ECI, because the occupational categories published for the ECI are broader than the occupational categories in the SOC. (ECI categorizes occupations at the 2-digit SOC level, while nurses are categorized at the 6-digit SOC level.)

There are two general issues with regard to changing SOC definitions. (1) the overlap of employment between series defined on the basis of 2000 SOC and 2010 SOC; and (2) the difference in compensation costs for the two sets of definitions, specifically, whether the change in cost due to the SOC change is within the range of what could be expected from sampling variation.

Table 4 shows that the reclassification of flight attendants from service occupations to transportation and material moving occupations had little effect on 2010 SOC-based employment in either occupational category. The change was approximately less than 2 percent in both categories. For registered nurses, the effect was somewhat larger, but still approximately less than 6 percent.

Table 4. Selected effects of reclassification from the 2000 Standard Occupational Classification system (SOC) to the 2010 SOC on employment in the Employer Costs for Employee Compensation estimates, private industry, December 2013

Occupational group	Percent of SOC 2000 occupational employment in SOC 2010	Percent of SOC 2010 occupational employment in SOC 2000
Service occupations	99.2	100.0
Transportation and material moving occupations	100.0	97.7

See footnotes at end of table.

Table 4. Selected effects of reclassification from the 2000 Standard Occupational Classification system (SOC) to the 2010 SOC on employment in the Employer Costs for Employee Compensation estimates, private industry, December 2013

Occupational group	Percent of SOC 2000 occupational employment in SOC 2010	Percent of SOC 2010 occupational employment in SOC 2000
Registered nurses	94.3	100.0

Source: U.S. Bureau of Labor Statistics, National Compensation Survey.

Table 5 provides information on the effect of adopting the SOC 2010 on civilian compensation costs. For each of the three occupational categories affected by the reclassification, table 5 shows whether the cost based on 2010 SOC definitions falls within the 90 percent confidence interval of the cost based on 2000 SOC definitions. If the compensation measure based on SOC 2010 is greater than the lower bound and less than the upper bound, then we can be 90 percent confident that the change in cost due to reclassification from SOC 2000 to SOC 2010 is no greater than what might happen because of the sample chosen.¹⁵ As the table shows, none of the estimates fell outside the confidence interval.

Table 5. Selected Employer Costs for Employee Compensation costs based on the 2000 Standard Occupational Classification system (SOC) and 2010 SOC, civilian workers, December 2013

Occupational group	Compensation measure	Cost per hour worked		Standard error	Confidence interval	
		SOC 2000 definition	SOC 2010 definition		Lower bound	Upper bound
Service workers	Total compensation	\$16.96	\$16.66	\$0.25	\$16.55	\$17.39
	Wages and salaries	11.98	11.84	.16	11.73	12.25
	Total benefits	4.97	4.82	.13	4.76	5.20
Transportation and material moving	Total compensation	25.36	26.04	.81	23.98	26.64
	Wages and salaries	16.69	17.00	.47	15.89	17.43
	Total benefits	8.67	9.04	.38	8.02	9.28
Registered nurses	Total compensation	49.51	48.66	.69	48.37	50.65
	Wages and salaries	34.62	33.83	.52	33.77	35.47
	Total benefits	14.89	14.83	.36	14.30	15.48

Source: U.S. Bureau of Labor Statistics, National Compensation Survey.

With the release of December 2013 estimates, the ECI introduced 2012 fixed employment weights to replace the 2002 fixed employment weights used from March 2006 to September 2013. As with the earlier weighting released with the March 2006 estimates, the new weights are based primarily on data from the BLS Occupational Employment Statistics survey. Changing the weights at approximately 10-year intervals preserves the analytical value of the Laspeyres index as a measure of change in labor costs over both the long run and varying subperiods. At the same time, BLS updated the SOC and NAICS classifications systems used in the ECI from 2002 SOC to 2010 SOC and from 2007 NAICS to 2012 NAICS. Reweighting and changes in SOC and NAICS classifications resulted in minimal disruptions to the historical continuity of the ECI. For the December 2013 seasonally adjusted series, existing seasonal factors were used for direct seasonal adjustment based on the continuity tests on the not-seasonally-adjusted data. With the March 2014 and subsequent revisions, the seasonal

factors will be based on 2002 weighted data up to the point of the reweighting and reweighted data thereafter. The methodology for indirect seasonal adjustment of aggregate series was modified to remove weight-change effects resulting from the reweighting. The method now includes an aggregation weight factor that was applied to the December 2013 estimates and must be recalculated and applied to subsequent estimates each year as part of the annual seasonal adjustment revision. The effects of the change from 2002 SOC to 2010 SOC on selected Employer Costs for Employee Compensation estimates were tested and found not to be statistically significant at the 90-percent confidence level.

Appendix: indirect seasonal adjustment aggregation adjustment factor

The formula for the indirect seasonal adjustment of a seasonal ECI series follows:¹⁶

$$\hat{A}_{jt}^{indirect} = \sum_i^{n_j} w_{ijt} \hat{A}_{ijt}$$

With the reweighting of the ECI in December 2013, the aggregation weights were updated to reflect new employment counts for the industry–occupation cells. Therefore, the aggregation weights for December 2013 (w_{ijt+1}) are not equal to the aggregation weights for September 20 (w_{ijt}). Without any adjustment, the September-to-December change across the weight revision would include both a cost-change effect and a weight-change effect for the indirect series:

$$\frac{\hat{A}_{jt+1}^{indirect}}{\hat{A}_{jt}^{indirect}} = \frac{\sum_i^{n_j} w_{ijt+1} \hat{A}_{ijt+1}}{\sum_i^{n_j} w_{ijt} \hat{A}_{ijt}} = \left(\frac{\sum_i^{n_j} w_{ijt+1} \hat{A}_{ijt+1}}{\sum_i^{n_j} w_{ijt+1} \hat{A}_{ijt}} \right) * \left(\frac{\sum_i^{n_j} w_{ijt+1} \hat{A}_{ijt}}{\sum_i^{n_j} w_{ijt} \hat{A}_{ijt}} \right).$$

cost-change effect weight-change effect

To ensure that the September-to-December change in an indirect seasonally-adjusted index reflects only the effect of the cost change, the December 2013 index was multiplied by an adjustment factor equal to $\left(\frac{\sum_i^{n_j} w_{ijt} \hat{A}_{ijt}}{\sum_i^{n_j} w_{ijt+1} \hat{A}_{ijt}} \right)$.

Thus, $Adjusted \hat{A}_{jt+1}^{indirect} = \sum_i^{n_j} w_{ijt+1} \hat{A}_{ijt+1} * \left(\frac{\sum_i^{n_j} w_{ijt} \hat{A}_{ijt}}{\sum_i^{n_j} w_{ijt+1} \hat{A}_{ijt}} \right)$.

After the adjustment to the December index, its change from the September index reflects the cost-change effect only.

$$\frac{Adjusted \hat{A}_{jt+1}^{indirect}}{\hat{A}_{jt}^{indirect}} = \left(\frac{\sum_i^{n_j} w_{ijt+1} \hat{A}_{ijt+1}}{\sum_i^{n_j} w_{ijt+1} \hat{A}_{ijt}} \right).$$

For each indirect seasonally adjusted series, the weight adjustment factor will remain constant, theoretically, for periods beyond $t+1$ (until a subsequent reweight) because it is based on the index values for September 2013. The weight adjustment factors will be revised slightly each March through 2018 because the seasonal factors for the directly-adjusted component series are revised each March as part of the ECI seasonal adjustment 5-year historical revision.

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NOTES

¹ For a more detailed discussion of the Employment Cost Index and its uses, see John W. Ruser, "The Employment Cost Index: what is it?" *Monthly Labor Review* (U.S. Bureau of Labor Statistics, September 2001), pp. 3–16, <https://www.bls.gov/opub/mlr/2001/09/art1full.pdf>; see also "Chapter 8. National compensation measures," *BLS Handbook of Methods* (U.S. Bureau of Labor Statistics), <https://www.bls.gov/opub/hom/pdf/homch8.pdf>.

² A Laspeyres index is an index that uses base-period quantities, such as employment counts, as weights to measure change over time. Because the weights are constant from year to year, indexes for a series can be compared over time.

³ Much of this article is based on three earlier articles discussing the shifts from the 1970–80, 1980–90, and 1990–2002 employment weights. For more information see Albert E. Schwenk, "Introducing new weights for the Employment Cost Index," *Monthly Labor Review* (June 1985), pp. 22–27, <https://www.bls.gov/opub/mlr/1985/06/art3full.pdf>; Albert E. Schwenk, "Introducing 1990 weights for the Employment Cost Index," *Compensation and Working Conditions* (U.S. Bureau of Labor Statistics, June 1995), pp. 1–5; and Stephanie L. Costo, "Introducing 2002 weights for the Employment Cost Index," *Monthly Labor Review* (U.S. Bureau of Labor Statistics, April 2006), pp. 28–32, <https://www.bls.gov/opub/mlr/2006/04/art5full.pdf>.

⁴ For more information on the OES program, see www.bls.gov/oes/home.htm. For more information on the QCEW program, see www.bls.gov/cew.

⁵ Includes data from both private industry and state and local government. Self-employed workers and farm and private household workers are excluded from private industry data. Federal government workers are excluded from the public sector.

⁶ Before March 2006, industries in the ECI were classified by the Standard Industrial Classification Manual, 1987 (Executive Office of the President, Office of Management and Budget, 1987) and occupations were classified by the 1990 *Standard Occupational Classification Manual*. See "Occupational Classification System Manual for the Employment Cost Index Survey Program," (U.S. Bureau of Labor Statistics, December 1993).

⁷ For a discussion of changes to occupational definitions for the SOC 2010 classification system, see Audrey L. Watson, "Implementing the 2010 Standard Occupational Classification in the Occupational Employment Statistics program," *Monthly Labor Review*, (U.S. Bureau of Labor Statistics, May 2013), pp. 36–49, available at <https://www.bls.gov/opub/mlr/2013/05/art3full.pdf>.

⁸ For example, Schwenk, "Introducing 1990 weights for the Employment Cost Index," p. 4, compared ECI indexes and percent changes obtained by using 1980 weights with those obtained by using 1990 weights and found little difference between the two sets of weights. For further analysis of the sensitivity of the ECI, see Michael K. Lettau, Mark A. Loewenstein, and Steve P. Paben, "Is the ECI insensitive to the method of aggregation? An update," *Monthly Labor Review*, December 2002, pp. 23–28, available at <https://www.bls.gov/opub/mlr/2002/12/art3full.pdf>.

⁹ It is difficult to determine at what point the difference between the fixed weights and more current weights is large enough to be important for economic analysis. The NCS program is currently investigating whether it would be appropriate to introduce new fixed weights more frequently than once about every 10 years.

¹⁰ For more information, see G. Donald Wood, "Estimation procedures for the Employment Cost Index," *Monthly Labor Review*, vol. 105, no. 5, May 1982, pp. 40–42, <https://www.bls.gov/opub/mlr/1982/05/rpt3full.pdf>.

¹¹ The 1970 and 1980 fixed weights for the ECI were derived from the Census of Population for those years. For the 1990, 2002 and 2012 reweighting, the primary data source was the Occupational Employment Statistics survey.

¹² If a series is not seasonal, the not-seasonally-adjusted index is used in the calculation.

¹³ Beginning with the March 2014 seasonal adjustment revision, seasonal factors will be estimated with the Census Bureau's X–13–ARIMA–SEATS program, with no change in the ECI seasonal factor estimation methodology. Comparisons of estimation results from X–12–ARIMA and X–13ARIMA–SEATS shows that the same results were obtained.

¹⁴ For a brief summary of seasonal adjustment of the ECI, see www.bls.gov/ncs/ect/ectsfact.htm. For a more in-depth discussion about ECI seasonal adjustments, see E. Raphael Branch and Lowell Mason, "Seasonal adjustment in the ECI and conversion to NAICS and SOC," *Monthly Labor Review* (U.S. Bureau of Labor Statistics, April 2006), pp. 12–21, <https://www.bls.gov/opub/mlr/2006/04/art3full.pdf>; see also E. Raphael Branch, "Changes in the publication of seasonally adjusted Employment Cost Index series," *Monthly Labor Review* (U.S. Bureau of Labor Statistics, March 2013), pp. 68–85, <https://www.bls.gov/opub/mlr/2013/03/art5full.pdf>.

¹⁵ For more information on constructing confidence intervals, see Albert E. Schwenk, "Measuring Trends in the Structure and Levels of Employer Costs for Employee Compensation," *Compensation and Working Conditions*, (U.S. Bureau of Labor Statistics, Summer, 1997), p. 14, <https://www.bls.gov/opub/mlr/cwc/measuring-trends-in-the-structure-and-levels-of-employer-costs-for-employee-compensation.pdf>.

¹⁶ For the formula for the indirect seasonal adjustment of an ECI seasonal series, see E. Raphael Branch, "Changes in the publication of seasonally adjusted Employment Cost index series," *Monthly Labor Review*, (U.S. Bureau of Labor Statistics, March 2013), p. 84, <https://www.bls.gov/opub/mlr/2013/03/art5full.pdf>.

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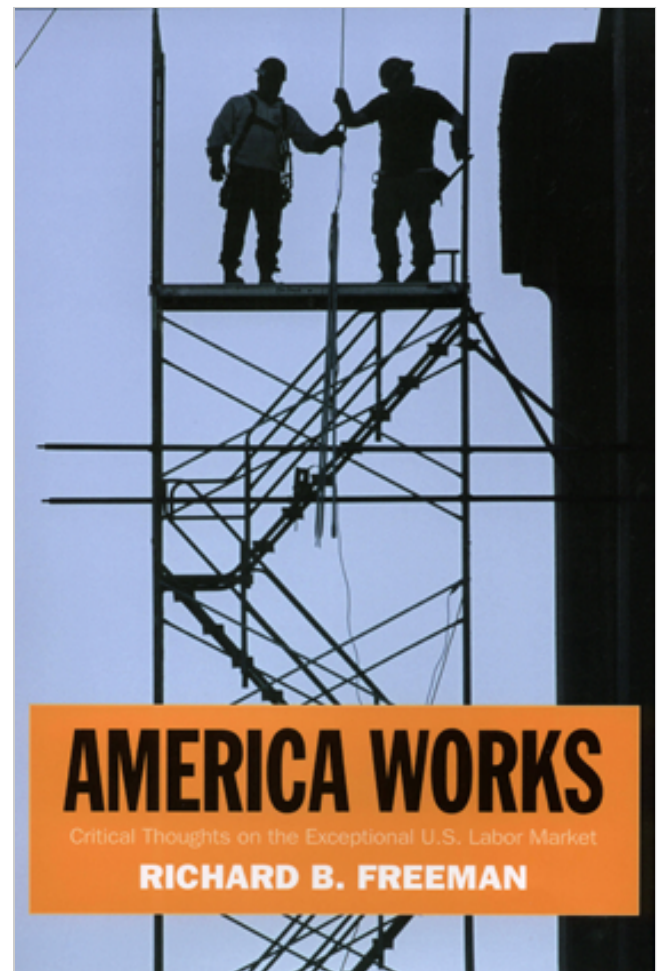
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May the invisible hand be with you: Can the U.S. market-driven labor system do better without reducing productivity and growth?

America Works: Critical Thoughts on the Exceptional U.S. Labor Market. By Richard B. Freeman. New York: Russell Sage Foundation, 2008, 191 pp., \$15.95 paperback.

In *America Works*, Richard B. Freeman takes us on a five-star tour of the United States labor market, laying out what is right and what is wrong with it in an entertaining and thoughtful manner. Freeman begins the book with a comparison between the United States and other advanced countries regarding how they determine pay, regulate the labor market, and provide social support to their workers. However, before getting into a “war of the models,” the reader has to understand how the U.S. labor market works, and Freeman does a splendid job explaining the American job system in the first two chapters. The American labor system has less institutional regulation than other major advanced countries have and provides U.S. workers with lower safety nets to deal with disability, unemployment, and health problems. The United States also relies more than other advanced countries (e.g., France and Canada) on decentralized wage setting to determine pay. There’s no question that the U.S. market-driven labor system diverges greatly from those in countries that make considerable use of collective bargaining (such as Canada, the European Union, and Japan, to name a few), but these differences have given the American labor market an extraordinary reputation. Freeman says that the U.S. job market is exceptional because it does not restrict the ability of businesses to make decisions (and therefore it does not restrict economic freedom), because it promotes mobility and job security, and because it has fewer labor regulations (relying basically on the country’s court system).

Freeman cites the statement “You’re fired”—Donald Trump’s famous catchphrase from the TV show *The Apprentice*—to illustrate the freedom of firms, and the song “Take This Job and Shove It” to depict the mobility of workers and the presence of job security in the American labor market. Americans are known for their



extraordinary mobility, not just across firms, but also across states. Market-driven economies do better than institution-driven systems in periods of great economic variability because markets are more flexible than institutions. This flexibility explains, in part, why, during the 1990s and the first decade of the 2000s, the U.S. labor system delivered high employment and an increase in productivity, in comparison to the labor systems of the country's European counterparts. The main source of high employment during that time came from women and immigrants. On the other side, productivity increases came from investing in education and in research and development, from skilled immigrants (engineers, scientists), and from automation of the economy, which experienced a shift from low-productive agriculture and less skilled manufacturing jobs to higher-value-added manufacturing jobs and knowledge-intensive jobs. The question that arises here is, Why has the American labor system failed to distribute the gains achieved from economic growth and rising productivity to workers in the form of rising real wages and benefits in the past couple of decades?

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In *America Works*, the author describes how inequality—defined as the differences in earnings across economic activities—“stole the cookie from the jar.” Institutionally driven wage systems tie productivity growth and wages together more tightly than does a market-driven labor system, so it is at this point that the reader starts wondering whether the most market-driven labor system fell short of the invisible-hand model in ways that institutions might correct. Why *are* earnings and income so unequally distributed in the United States? One reason is that earnings among unionized workers, whose wages are set by collective bargaining, and the earnings of public-sector workers, whose wages are set by governments or through collective bargaining, are less dispersed than the earnings of otherwise comparable workers in the nonunion private sector and, as is common knowledge, union membership has been declining steadily for years. Freeman estimates that the decline of unions accounted for perhaps 20 percent of the rise in inequality in the country. Another institutional force that affects inequality is the minimum wage, an issue currently being debated both at the national and state level. Among the variety of proposals suggested by the author are two kinds: those aimed at helping workers and firms, such as increasing spending on research and development, implementing financial incentives for students in science and engineering, and increasing profit sharing and employee stock ownership; and those aimed at improving “property rights” of workers—for example, offering union membership by industry or geographic area rather than by company and granting tax breaks to companies offering stock options to workers proportionate to their income.

The book uses charts to visualize the U.S. labor market's position in relation to the labor markets of other economies, both advanced and otherwise. Freeman makes use of data from the Current Population Survey (CPS) to discuss earnings and labor force participation rates. He highlights the fact that the CPS earnings survey understates the increase in earnings for high-income earners; in other words, people who earn more than \$150,000, whether it be \$1 million or \$10 million, are classified simply as earning more than \$150,000, rather than by the actual amount that they earned. Freeman also mentions that the earnings data fail to include stock options, which constitute a major part of the compensation package for top executives. Although I am generally sympathetic to both the analysis and the conclusions presented in *America Works*, I have to admit that I found the chapter which includes all the proposals lacking in detail.

So, should you read this book? The answer is yes: chapter after chapter, the author brings the reader along for a ride into the mystery of why earnings haven't gone up when productivity and real wages are supposed to rise together in a market economy—and in trying to solve this dilemma, *America Works* provides a compelling plan for how we can ensure that markets will work better for all Americans.

One hundred years of Current Employment Statistics—the history of CES sample design

To help mark the Monthly Labor Review's centennial, the editors invited several producers and users of BLS data to take a look back at the last 100 years. Since its inception in 1915, the Current Employment Statistics (CES) survey has undergone significant enhancements, including improvements to sample design. When the size of a population makes a census impractical, a representative subset of the population—a sample—is used to estimate characteristics of the population. It is important that the sample be representative of the population. The methodology that is used to select a representative sample from a population is perhaps the most critical step in designing a survey. This article discusses the evolution of the CES sample design.

In October 1915, what is now known as the Current Employment Statistics (CES) survey published employment and payroll data for four manufacturing industries—boots and shoes, cotton goods, cotton finishing, and hosiery and underwear—using data collected from fewer than 200 large manufacturing firms. The program gradually expanded in sample size and industry coverage over several decades, with the last major sample size expansion completed in the mid-1980s. This increase was undertaken, specifically, to provide adequate sample to expand publication detail in the services industries. As a result, and after 100 years of research, testing, and survey improvements, the CES program now surveys approximately 146,000 businesses and government agencies to estimate employment, hours, and earnings of workers on nonfarm payrolls. Since these businesses and agencies may have more than one physical location, they cover approximately 623,000 individual worksites.¹



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Origins and evolution of the CES sample design

In its infancy, the CES program first published estimates without a formal sample design. Soon after, CES started partnering with state workforce agencies (SWAs), beginning in 1916 with the state of New York, to conduct the CES as a federal–state cooperative program. This meant that firm data collected by individual states would be

shared with CES for the production of estimates at the national level. Other states gradually joined the cooperative program, and, by 1949, all states had agreements with CES. CES provided funding and estimation guidelines, and states collected sample data and produced state-level estimates. Before all states were covered in the cooperative program, CES collected data and made estimates for nonparticipating states.

The inception of the survey predated the development of probability sample design as an internationally recognized standard for sample-based surveys. It is not entirely clear how sample size or selection were determined in the early years, although later documentation referred to the early CES as a “collection of cut-off samples” by industry. Cut-off samples deliberately exclude a portion of the population that is being measured; CES empirically derived these cut-offs over time using research on what sizes and types of samples yielded satisfactory results when compared against administrative benchmark sources.²

Although some of the historical details are not available, it is clear that for the first few decades of the survey there was no formal sample design. What did exist was a strategy to sample enough units to achieve a high percentage of universe employment coverage. The early decades of the CES program focused mainly on producing employment and payroll data for manufacturing industries; hence, the main sample-coverage strategy was to sample as many of the largest manufacturing firms as possible. This strategy apparently worked well enough at the time, because manufacturing industries were mostly dominated by large firms. However, once industries in the services sector began to represent a larger portion of national-level employment, there was a demand for published data in these industries as well. Many of these service-sector industries were dominated by smaller firms, and it was not as straightforward to achieve a representative sample by including just the largest firms. This issue likely helped launch the effort by CES researchers to develop new sampling guidelines in the 1940s.

The 1940s sampling memorandum series

In the late 1940s, BLS researchers began a series of tests with a goal of developing a more rigorous approach to sampling. These tests and results from testing several sample selection and estimating procedures were documented in a series of seven sampling memorandums. An important caveat was that most of the research encompassed only five manufacturing industries: cotton goods, meat packing, electrical equipment, shipbuilding, and newspapers and periodicals.

These are the major conclusions from the sampling memorandums:

- *Sampling memorandum no. 1, May 1947.* The use of an unrestricted random sample³ with a “blow-up” estimator⁴ worked poorly for estimating industry employment. It required a sample of 90 percent or more of the universe in order to achieve acceptable results, where acceptable results were defined as a 2-percent error at a 95-percent confidence interval.
- *Sampling memorandum no. 2, November 1947; and memorandum no. 3, December 1947.* A random sample with a ratio estimator (or an estimator that uses the relationship between two variables) was determined to be preferable to the blow-up estimator for most industries because it required a smaller sample size to achieve the same level of sampling error.⁵ This held if the coefficient of variation (or the ratio of the standard deviation to the mean) was greater than 0.5, which was the case for each of the tested industries with the exception of the shipbuilding industry.

- *Sampling memorandum no. 4, April 1948.* Stratification, or the dividing of the population into subpopulations by size of establishment, greatly reduced variance (how far the data are spread out) and therefore the required sample size. The tests reported in this memo divided the sample into two size strata: large and small. The strata boundaries were empirically determined by trying different boundaries to see which resulted in the smallest possible sample for a given level of variance. The large size stratum was a take-all sample, where all units are included in the sample, and the small size stratum was an unrestricted random sample with a blow-up estimator. Results from the two strata were added together to arrive at the industry-level employment estimate.
- *Sampling memorandum no. 5, July 1948.* An estimate developed from two size strata with a ratio estimator generally outperformed an estimate made using a blow-up estimator. In this iteration, one nonmanufacturing industry, miscellaneous retail trade, was included in the testing.
- *Sampling memorandum no. 6, November 1948.* Tests with sampling proportional to size, in which the selection probability of each unit is set to be proportional to its size, proved a much less efficient allocation of the sample than using a take-all approach for the large size class. Tests also were conducted using an optimum allocation method that minimized sampling error for the sample sizes being considered. This basically resulted in the same conclusions as sampling memo 5, indicating a take-all approach for the larger size class worked best to minimize variance.
- *Sampling memorandum no. 7, March 1949.* This memo reported on the results of additional tests of drawing samples and making estimates for the original five manufacturing industries. It concluded that use of ratio estimators for samples allocated proportionately across two strata was not consistently better than use of a ratio estimator based on an unrestricted random sample.

A followup internal memorandum in 1950 presented results of a series of additional tests. These tests used hypothetical data with a universe of five establishments and a sample of three establishments to illustrate variance and bias (or error from the sampling, collection, or estimation processes) of different sample designs and estimators. The same designs and estimators that were tested in memorandums 1–7 were used, and the results illustrated the same conclusions that had been reached using the empirical data.

While this series of memos set the stage for the CES program's use of a certainty size class for large establishments and the use of a ratio estimator, internal memos and American Statistical Association (ASA) papers recognized that ratio estimators contained bias and that there was an overall downward bias in CES employment estimates.

1964 sample redesign

A June 1963 internal paper titled “Analysis of BLS-790 sample with a proposal for a new sample design” was the catalyst for the first formal updates to sampling methods since the principles that were set out in the 1940s sampling memo series. The analysis was undertaken because there were newly available employment tabulations for 1959 by establishment size from the benchmark source for CES—the BLS ES-202 data.⁶ This marked the first comprehensive set of ES-202 data by size class. The analysis reinforced major conclusions from the sampling memo series. The most notable conclusion was that most industries were dominated by either large or small firms and, therefore, would have a skewed distribution by firm size. The analysis also reaffirmed that a form of optimal allocation—two size strata and a ratio estimator—would work well for most industry series. These conclusions

were based on empirical observation and experimentation using the ES-202 data. The research tested a “full stratification” by 4-digit Standard Industrial Classification (SIC) and eight size strata, but the resulting 32-cell framework was considered impractical, as it would be too difficult to adequately populate all the estimating cells. As a result, cells were collapsed to yield a more practical design.

The 1963 paper recommended retaining all current sample members because of the cost, risk, and difficulty of attempting to solicit an entirely new sample. Because the new sample design would have retained the current sample, rather than using a randomly selected sample, it would not qualify as a probability sample. This meant that standard sampling variances could not be calculated, nor could standard inferences be made about the reliability of the resulting estimates. Additional recommendations were also developed on the basis of what was considered practical within existing resources. For example, if an industry was dominated by large firms (where 90 percent or more of its employment was in establishments with 250 or more employees), there was no sampling of firms with 0–19 employees; the overall sample coverage goal was determined to be 50 percent of universe employment. For industries dominated by small firms (where 75 percent or more of employment was in establishments with 10 or fewer employees), empirical experiments suggested that a 5-percent employment universe coverage was sufficient.

The paper concluded that this new design would be an improvement over the old cut-off sample design, since it laid out a balanced representation across all size classes while giving more weight to larger establishments, and because every unit would have a known probability of selection. The new design was considered a step toward a probability sample, but not an actual probability sample. The paper also concluded that the existing sample coverage in manufacturing appeared to be adequate for reliable estimates and approximated an optimum allocation design, but that many of the nonmanufacturing industries had inadequate samples.

CES began implementing the proposed new design from the 1963 paper in July 1964 with the issuance of a memorandum to regional commissioners and contract state agencies titled “BLS Employment Instructions No. B-29 New Sampling Procedures.” This memo contained a set of sampling tables by SIC (4-digit SIC code in manufacturing and 3-digit SIC code in nonmanufacturing) and six size classes. The tables contained ratios that each state was to apply against ES-202 universe listings to determine sample sizes for each industry/size stratum. The sampling ratios were based on an assessment of sample needed for reliable national estimates, but did not specify requirements for state or area estimates.

The memo described this design as a “close approximation” to a form of optimum allocation known as “probability proportionate to size” (or to the average size of establishment, in the case of CES). The design distributed a predetermined number of establishments in the total sample among sampling cells on the basis of the ratio of employment in each cell to total industry employment. Within each cell, establishments were to be randomly selected (with the major exception that existing sample units should be retained). In practice, this meant that if a cell had, for example, 20 percent of universe employment at the industry level, then it would receive 20 percent of the sample units for that industry. For most industries, the take-all stratum was set at 250 employees at the establishment level. If 90 percent or more of an industry’s employment was in the two largest size classes, the rule was to take all from those cells and sample no others. If less than 10 percent of the universe employment was in establishments with fewer than 20 employees, the rule was to take no sample from establishments with fewer than 20 employees.

States were instructed to begin implementing this new design immediately, although it was noted that there were insufficient resources to fully implement the design. The existing CES sample totaled 107,000 establishments, while the new design, if fully implemented, would yield a sample of 148,000. States also were instructed to direct sample solicitation efforts to areas of greatest need. It was also noted that thereafter sample adequacy should be reviewed after each annual benchmark and solicitation efforts directed toward those industries with the greatest sample deficiencies.

The 1964 sample redesign was an improvement to the previous CES sampling methods, but the redesign also contributed to the subsequent, decades-long criticism that the CES sample was potentially unrepresentative of the universe because it was not a true probability-based design. Moreover, critics noted that it was skewed toward including large firms at the expense of small firms.

1970s and 1980s quota sampling design and procedures

Sample initiation and most sample collection continued to be the responsibility of each of the 53 SWAs in the federal–state cooperative program through the 1980s.⁷ Sample requirements developed by CES, in the form of ratios by industry and size (for example, select 1 out of every 10 establishments), were given to the SWAs. The original sampling ratios were developed for the 1964 memorandum cited above; later these ratios were commonly known as “G-1”—the appendix in the CES State Operating Manual that contained the ratio tables.

Individual SWAs were responsible for sample solicitation, maintenance, and monthly collection. Adherence to the quotas in G-1 was not regularly enforced or measured by CES. States were instructed to review and update their sample annually, after benchmarking, on the basis of a comparison of existing sample size versus the G-1 requirements and benchmark revision magnitudes. Each state decided for itself how large a sample it could support within its resources.

During the 1970s and 1980s, the quota sample method established in 1964 continued, basically unchanged. A few modifications were made on the basis of empirical experimentation, although there is no available record of this research. A minimum of 15 establishments or 50 percent universe sample coverage was set for all basic estimating cells. A second set of ratios, known as appendix G-4, was developed and used as a guideline for sample adequacy for statewide and metropolitan statistical area (MSA) estimates, though the origins of these ratios are unclear. Appendix G-4 contained two separate algorithms, one for states and MSAs with total nonfarm employment of at least 500,000 and one for those with total nonfarm employment of less than 500,000.

States were encouraged to oversample on the basis of their previous experience in order to account for nonresponse. If they generally had a success rate of 25 percent in soliciting new units, states were directed to sample 4 times as many units as the ratio tables called for. States were also directed to examine the magnitude of statewide and MSA benchmark revisions to determine which industries or areas might be most in need of sample supplementation.

Though the sample design did not change, the sample size greatly expanded during the 1980s. States were directed to solicit as many additional sample units as possible so that CES could expand its published series in the service-providing industries, as recommended by the 1979 Levitan Commission.⁸ The sample size grew from approximately 160,000 establishments in 1975 to 425,000 establishments by 1989. The total sample size has remained nearly unchanged since then; however, the design was changed to a probability-based sample during

the CES redesign that began in 1995. To create a true probability sample, the redesign resulted in the cancellation of thousands of existing sample members and solicitation of thousands of new ones.

Motivation for change to probability sampling

Quota sampling is at risk for substantial bias; in contrast, the random selection technique inherent in probability sampling provides a measure of protection from bias. A random sample is more likely to be representative of the universe because a random selection balances out both the known and unknown characteristics of a population.

Probability sampling had been the standard for sample surveys for more than 50 years before it was adopted by CES. CES had not previously converted mainly because of the time, the expense, and the risk to ongoing operations required to change a massive, ongoing, monthly survey. Many people, both inside and outside of BLS, believed the existing sample was working well, since it generally experienced small to moderate-size benchmark revisions at the total nonfarm level for the national and statewide estimates and retained a high universe coverage (over one-third of total nonfarm employment).

A BLS-commissioned study of the CES program by a special panel of the American Statistical Association issued a report in 1994 that had, as a primary recommendation, the adoption of a probability sample design. BLS had commissioned this panel after an unusually large benchmark revision for March 1991 that caused extreme concern among major data users and within BLS. Although CES sample design deficiencies were not found to be the cause for this large benchmark revision, this report helped provide the incentive for CES to begin work on a new sample design.⁹

In addition, internal CES research from the mid-1990s demonstrated the bias inherent in the existing quota sample by comparing the age distribution of firms in the CES sample against the age distribution of establishments in the universe for 10 large states. On average, the CES sample units were approximately 10 years older than the universe as a whole. This research also simulated estimates made for the continuing sample units' portion of the universe, using the existing CES sample.¹⁰ The results showed very large benchmark revisions, indicating that the existing CES sample was not performing well and that techniques such as bias adjustment (at the national level) and manual data interventions (at the state and MSA levels) were being used to override sample results to a large degree. These techniques were used in an attempt to compensate for the nonstandard sample design, as well as to account for business births. Historically, these techniques had varying degrees of success, as demonstrated by the varying sizes of benchmark revisions. This research helped convince the SWAs, as well as BLS top management, that quota sampling was no longer viable.

On the basis of its internal research results and the ASA report, CES undertook an extensive research effort to develop the most optimal sample design that would be both affordable and technically defensible. CES included outside experts in survey design and estimation in its research. These experts included senior statisticians from Westat (a private research firm), the National Opinion Research Center at the University of Chicago, and the University of Michigan Survey Research Center.

As part of the research, simulations were completed for all states and distributed to SWAs to familiarize them with expected results from a new sample design. Additional work was completed on improving sample solicitation and data collection techniques needed to sustain an adequate response rate. Extensive research was also completed

on estimation algorithms and on sampling new business births in real time versus modeling for their contributions to total employment.

Current probability sample design

Development of the CES probability sample design began in 1995, was completed in 1997, and was production tested between 1998 and 2002. The implementation of the new sample design into production was phased in between June 2000 and June 2003, following successful production tests. Each June, one or more major industry divisions were converted to the new sample at the time of the annual benchmark revision. Wholesale trade was converted in 2000; mining, construction, and manufacturing in 2001; transportation and public utilities, retail trade, and finance, insurance, and real estate in 2002; and finally, services in 2003. At the time, the industry classification system was SIC—the precursor to the North American Industry Classification System (NAICS).

Since CES was already obtaining near universe coverage for federal and state government, a probability sample for government was not developed. Local government is a possible candidate for future conversion to a probability sample, although coverage in that sector is also very high. The current local government sample is a legacy sample from the old quota sample design, when individual states were responsible for sample selection and collection.

Sample size and allocation by state

As a starting point, the first CES probability sample (drawn in 1998) set the new probability-based sample size to be equal to the existing quota sample size for each state. This was done to obtain the cooperation of SWAs in the transition to a new design and to preserve the approximate overall sample coverage. BLS also determined that this was the total sample size that the program resources could support. This effectively resulted in a state-based design.

During the sample redesign research phase, both national and MSA-based designs were also considered; however, the state-based design was found to be the most efficient in terms of balancing several program goals. A national design would require very little sample from the smallest states, leaving them with unacceptably large variances. By contrast, an MSA-based design would be very inefficient for producing national estimates and would increase sampling error to an unacceptable degree. The top two priorities for the CES program are reliable all-employee estimates at the national and statewide levels, followed by MSA-level estimates. A state-based design was determined to be the best option to satisfy these competing priorities.

State sample reallocations

Approximately 5 years after the initial CES redesign was completed, BLS reevaluated the sample size and its distribution across states for the first time and completed a relatively minor reallocation across states. The total sample size was slightly increased at this time. The sample review examined several possible methods for determining the sample distribution across states. One method involved equalizing relative standard errors (RSE) across states. This approach was deemed unacceptable because it resulted in a large increase in variance for national and large states' estimates. CES also examined an unbounded optimum allocation to produce a national total nonfarm employment estimate with the smallest sampling error. This approach was unacceptable because it substantially increased variance for smaller states. The final allocation selected was a bounded, national optimum allocation, which specified upper limits on states' RSEs and limits on how much sample any individual state could

lose. The maximum loss was set at 15 percent, and the resultant national RSE of .075 percent was considered acceptable. The practical effect of the reallocation was primarily to reallocate sample toward employment-growth states and away from states with declining employment. The final allocation is close to a proportional allocation, where each state's allocation is approximately equal to its proportion of national total nonfarm employment (with minimum sample limits set for the smallest states).

Another minor reallocation was completed in 2011 on the basis of similar principles. CES plans to continue to review and reallocate the sample across states approximately every 5 years.

Sampling methods

The CES sample is a stratified simple random sample of worksites clustered by unemployment insurance (UI) account number. It is a state-based design where each state is assigned a fixed sample size, and then an optimum allocation procedure is used to allocate the total sample across CES supersectors¹¹ and size classes to achieve the maximum level of reliability for the total nonfarm employment estimate for the state.

In general, an optimum allocation distributes a fixed number of sample units across a predetermined set of strata to minimize variance (also known as sampling error) on the primary estimate of interest. For CES, the primary estimate of interest is the total nonfarm monthly employment change. The optimum allocation assigns more sample in cells for which data are less costly to collect, cells that have more units, and cells that have a larger variance. The sampling rate for each cell is a result of the optimum allocation.

Timing and procedures for sample updates

The entire sample is redrawn annually in the fall of each year from the most recent first-quarter Longitudinal Data Base (LDB), which is a longitudinally linked database file from the CES administrative benchmark source—the BLS Quarterly Census of Employment and Wages. This update incorporates new business births and updates control information on industry and geographic classifications for existing firms. The annual update also removes business deaths from the frame. In addition to the annual full sample redraw, a sample of new business births is drawn midway through each year. The sampling frame for births includes only those firms born since the first-quarter sample draw.

These updates keep the sample as current as possible with respect to business births and deaths. Until 2014, about 1 full year separated the annual sample draw and the introduction of the sample into live monthly estimates; this time was needed to complete sample refinement, enrollment, collection, and validation of initial reported data values. As an example, monthly estimates for January through December 2013 were made using sample selected from the 2011 LDB file. Beginning in August 2014, the annual updates were introduced under a quarterly sample implementation pattern by supersector that allows the sample to be included in estimation once the enrollment for the supersectors is completed. There is still a lag in the sample availability, relative to the current month's estimate; however, quarterly implementation decreases that lag compared with the previous annual sample implementation.

Because of the lag in picking up business births and deaths in the live monthly production sample, CES uses a model-based technique to account for the contribution of recent business births and deaths in the monthly estimates. For more information on the CES birth/death model, see <https://www.bls.gov/web/empisit/cesbd.htm>.

Because of the cost and workload associated with enrolling new sample units, all units remain in the sample for a minimum of 2 years. To ensure that all units meet this minimum requirement, CES established a “swap” procedure. This procedure allows units to be swapped into the sample that were newly selected during the previous year but not reselected as part of newly drawn sample for the current year. The procedure removes a unit within the same selection cell and places the newly selected sample from the previous year back into the sample. Approximately two-thirds of the drawn sample overlaps from one year to the next, much of it in the large size classes.

As another practical consideration, most firms are kept in the sample for no more than 4 years, except for certainty size class reporters. This is done to minimize respondent burden and help elicit cooperation when a firm is first solicited for the CES survey.

The CES sample is drawn at the UI account level within each state, but CES collects data at the establishment level within each UI account whenever possible. The establishment-level breakouts are primarily an aid in making more accurate MSA estimates. Some UI accounts contain establishments with multiple industry (NAICS) codes, and thus the establishment-level breakouts contribute to more accurate industry estimates as well at national, statewide, and MSA levels. For firms that do not provide worksite-level breakouts, a disaggregation method known as proration is used to distribute the UI account-level data to the worksite level.

Sample coverage by industry

The latest benchmark employment levels and the approximate proportion of universe employment coverage at the national total nonfarm level and at NAICS supersector levels can be found on <https://www.bls.gov/web/empsit/cestn.htm#Tb1>. The sample distribution by industry reflects the goal of minimizing the sampling error on the total nonfarm employment estimate, while also providing for reliable estimates by industry. Sample coverage rates vary by industry as a result of building a design to meet these goals.

Conclusion

The modern-day CES program evolved from one that began 100 years ago, when employment estimates were published for four manufacturing industries before there was a formal sample design. Through research, testing, and cooperation with state partners, the program has undergone significant improvements in sample design that have not only improved reliability of the estimates, but also helped make CES data one of the world’s most-watched principal federal economic indicators. Those improvements include increased coverage to better represent the economy, enhanced representation of both small and large firms, and reduced costs and respondent burden. Today, the CES sample is a stratified, simple random sample of UI accounts (and all of their associated establishments), a design that reflects contemporary standards for sample-based surveys.

SUGGESTED CITATION

Laura A. Kelter, "One hundred years of Current Employment Statistics—the history of CES sample design," *Monthly Labor Review*, U.S. Bureau of Labor Statistics, August 2016, <https://doi.org/10.21916/mlr.2016.35>.

NOTES

¹ The Current Employment Statistics (CES) program provides detailed industry data on employment, hours, and earnings of workers on nonfarm payrolls. For more information on the program’s concepts and methodology, see “Technical notes to establishment survey

data,” <https://www.bls.gov/web/empsit/cestn.htm>. To access CES data, see “Current Employment Statistics—CES (national),” <https://www.bls.gov/ces>.

2 Benchmarking is a process of aligning sample estimates with population values, usually from an administrative data source.

3 An unrestricted sample is a sample in which units can be selected with equal probability, and because sample units can be selected more than once, they can be replaced.

4 Despite research efforts, the CES program was unable to find the specifics of the “blow-up” estimator tested in sampling memorandum no. 1. Consensus among program experts is that the method was a form of a Horvitz-Thompson estimator. See D.G. Horvitz and D.J. Thompson, “A generalization of sampling without replacement from a finite universe,” *Journal of the American Statistical Association*, December 1952, pp. 663–685, <http://lib.stat.cmu.edu/~brian/905-2008/papers/Horvitz-Thompson-1952-jasa.pdf>.

5 Sampling error is the error resulting from observing a sample rather than the entire population.

6 The ES-202, now known as the Quarterly Census of Employment and Wages (QCEW) program in BLS, became the administrative benchmark source for the CES program in 1935. Employers are required to regularly report employment and payroll data to this program.

7 There are a total of 53 state workforce agencies, but only the 50 states and the District of Columbia contribute to national total nonfarm employment.

8 The Levitan Commission, also known as the National Commission on Employment and Unemployment Statistics, was founded to examine the government’s labor force statistics and recommended that the programs be reviewed at least once each decade.

9 The large revision was actually caused by a reporting change by payroll processing firms in their development of employment counts submitted to the QCEW program for benchmarking. The ASA panel validated this conclusion by CES.

10 Continuing units are defined as all units, excluding births (new) and deaths (those going out of business).

11 The CES survey publishes estimates for aggregated NAICS sectors called “supersectors.”

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Injuries from falls to lower levels, 2013

Falls to a lower level accounted for nearly 5 percent of all worker injuries and illnesses requiring days away from work in 2013 and for 13 percent of all fatal work-related injuries. This article compares the numbers of such falls with data from 2011, looks at three industries with a high incidence of falls, distinguishes between fatal and nonfatal falls, and briefly discusses the occupations and demographics of workers who fall to lower levels.

Falls to lower levels in 2013 were a major hazard to workers. Workers in private industry, state government, and local government suffered 57,020 injuries resulting in days away from work because of falls to lower levels, and 595 workers across private industry and all levels of government lost their lives because of such falls. Falls to lower levels accounted for nearly 5 percent of all injuries and illnesses that required days away from work and for 13 percent of all fatal work-related injuries. The falls resulting in nonfatal injuries required that workers take a median 20 days away from their job, more than twice as long as the 8 days for all nonfatal injuries and illnesses.

In contrast, falls on the same level accounted for more injuries with days away from work, but fewer fatal injuries. In 2013, there were 185,230 cases with one or more days away from work due to falls on the same level. Falls on the same level resulted in 110 fatal injuries.

The number of nonfatal falls to a lower level has been mostly unchanged in private industry since 2011 (see table 1), while the number of fatal falls to a lower level for private industry has increased slightly, from 522 in 2011 to 569 in 2013. Most of this change was in the private construction industry, whose fatal falls increased from 255 to 291, or 14.1 percent, from 2011 to 2013. During this period, total hours worked in the private construction industry increased by 5.8 percent.



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Table 1. Falls to a lower level, wage and salary workers, 2011 to 2013

Year	Nonfatal injuries		Fatal injuries		
	Private industry	State and local government	Private industry	State and local government	Federal government
2011	47,920	10,150	522	25	5
2012	47,200	9,690	548	17	4
2013	47,120	9,900	569	18	8

Note: The scope of workers included in the Survey of Occupational Injuries and Illnesses differs from that included in the Census of Fatal Occupational Injuries. The Survey of Occupational Injuries and Illnesses excludes self-employed workers, federal government workers, and workers on farms with fewer than 11 employees; the Census of Fatal Occupational Injuries includes such workers.

Source: U.S. Bureau of Labor Statistics.

The Bureau of Labor Statistics (BLS) collects data on occupational injuries and illnesses and on fatal occupational injuries; however, the program is a purely statistical one and has no regulatory functions. The Occupational Safety and Health Administration (OSHA) is responsible for ensuring workplace safety. To support this mandate, OSHA creates safety standards and is responsible for enforcing those standards. In the construction industry, fall protection is required when workers are at heights 6 feet or more above a lower level.¹

In some circumstances, such as proximity to dangerous equipment, protection is required at heights less than 6 feet. Some examples of fall protection are guardrails, safety nets, and fall arrest or harness systems.

Data on nonfatal occupational injuries and illnesses come from the Survey of Occupational Injuries and Illnesses (SOII).² Fatal injury data come from the Census of Fatal Occupational Injuries (CFOI).³

New data collected on height of fall

Data collected by the SOII and CFOI have been coded, beginning with survey year 2011, on the basis of the Occupational Injury and Illness Classification System (OIICS), version 2.01. This classification system is a comprehensive revision of the coding system used from 1992 to 2010. The new system encompasses a break in series, so data from 2011 to 2013 are not directly comparable to data from 1992 to 2010.⁴

In the OIICS system, the event or exposure (such as fall to a lower level) describes the manner in which the injury or illness was produced or inflicted by the source of injury or illness. Beginning with 2011 data and OIICS 2.01, falls to a lower level were subcategorized as follows:

- Fall to lower level, unspecified
- Fall from collapsing structure or equipment
- Fall through surface or existing opening
- Other fall to lower level

Each of those categories was further divided by the height of the fall, if known or reported, in 5-foot increments (for example, 6 to 10 feet) up to 30 feet. All falls to a lower level from greater than 30 feet were recorded as “more than 30 feet.” The object or structure the worker fell from (roof, ladder, etc.) was captured not by the event code but by the source code. For falls to a lower level, the source was the equipment or part of the structure (structural

element) from or through which the worker fell. In some cases, a secondary source was recorded; this was the object or substance, if any, that contributed to the worker's fall. In the example of a worker falling from a ladder, the secondary source could be the floor or ground. In 84.8 percent of the nonfatal falls to a lower level in 2013, the secondary source was not specified.

As the height of the fall increases, fatal injuries represent a higher proportion of the total of fatal injuries and days-away-from-work injuries. While this result is hardly surprising, data collected from the SOII and CFOI allow rough comparisons of the risks workers face in situations where falls are a hazard.

The comparison is not perfect, as only falls that result in a fatal injury or an injury with one or more days away from work are considered. BLS has limited data on falls that result in injuries with job transfer or restriction (from a pilot study focusing on a small number of industries⁵) and no data on falls that result in injuries without lost work time or with no recordable injury. In addition, the scope of the CFOI and SOII is not the same: the SOII excludes self-employed workers, as well as workers on small farms with 10 or fewer employees.

It is also difficult to compare event or exposure codes because some cells contain data that are not publishable for the SOII, the CFOI, or both. Falls to a lower level are classified as fall to lower level, unspecified; fall from collapsing structure or equipment; fall through surface; and other fall to lower level. Falls to lower level, unspecified, are cases of falls where not enough information is available to code at a more detailed level. Other falls to lower level, the majority of falls to lower level, include falls other than from a collapsing structure or equipment or through a surface. Some examples are falls from a ladder, roof, scaffold, stairs, or trees. This article focuses on other falls to lower level (code 433) because 76.7 percent of the injuries and 78.2 percent of the fatal injuries are within in that group. For both the SOII and the CFOI, the article focuses on falls in the private sector, and, for the CFOI, it excludes self-employed workers. This approach brings the scope of workers covered by the CFOI and SOII closer but still not equal, as the SOII excludes workers on small farms. The agriculture industry, however, represents a small portion of the fatal-falls-to-lower-level total. Of the 322 falls coded as "other fall to lower level" among wage and salary workers, only 1.2 percent were in the animal production or crop production industries.

Within the subset of "other falls to lower level" among wage and salary workers in private industry, the height of the fall is specified in most (87.3 percent) of the fatal injury cases. For injuries with days away from work, the height is specified in about half (49.4 percent) of the cases. The CFOI collects information from multiple sources, including death certificates, workers' compensation reports, and other reports provided by state administrative agencies. On average, the CFOI collects four documents from different sources for each fatal injury, while the SOII relies only on the information provided by the survey respondent to code cases. The additional information may explain why fatal fall injuries are more often coded at a higher level of detail.

In this subset of injuries due to falls, there were 280.0 days-away-from-work injuries for every fatal injury when the fall was from less than 6 feet. (See table 2.) When the fall height was between 26 and 30 feet, there were 3.5 days-away-from-work injuries for each fatal injury. For falls from heights greater than 30 feet, there were 50 fatal injuries while the number of days-away-from-work injuries did not meet publication criteria.

Table 2. Fatal occupational injuries and nonfatal occupational injuries involving falls to a lower level, private wage and salary workers, 2013

Event	Injuries requiring days away from work	Median days away from work	Fatal injuries	Ratio of days-away-from-work injuries to fatal injuries
Falls to lower level	47,120	21	423	111.4
Other falls to lower level ⁽¹⁾	36,130	20	322	112.2
Other falls to lower level less than 6 feet	14,280	17	51	280.0
Other falls to lower level 6 to 10 feet	2,310	60	31	74.5
Other falls to lower level 11 to 15 feet	520	60	59	8.8
Other falls to lower level 16 to 20 feet	540	180	39	13.8
Other falls to lower level 21 to 25 feet	130	100	34	3.8
Other falls to lower level 26 to 30 feet	60	17	17	3.5
Other falls to lower level more than 30 feet	—	—	50	—

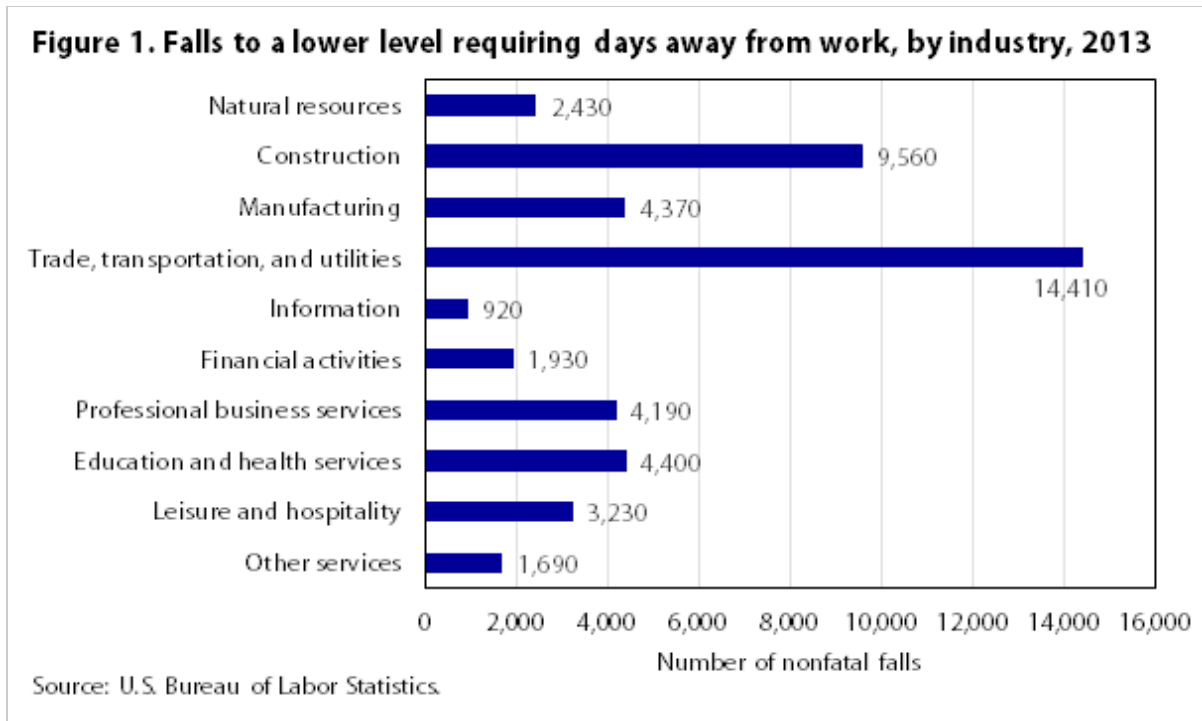
Notes:

⁽¹⁾ This category includes all falls to a lower level other than falls from a collapsing structure or equipment and falls through a surface or existing opening.

Source: U.S. Bureau of Labor Statistics.

Nonfatal injuries by industry

The SOII collects data annually from a random sample of employers. For cases with days away from work, more detail is available, including worker demographics, temporal characteristics, and descriptions of the cases and how they occurred. This article describes injuries requiring days away from work because of falls to a lower level. The term “fall injuries” could also include injuries that require job transfer or restriction and injuries that are recordable but do not involve lost work time, as well as injuries resulting from a fall on the same level. The article focuses only on injuries resulting from falls to a lower level and requiring days away from work, and will refer to these as “fall injuries” in the interest of brevity.



Most of the fall injuries occurred in private industry (82.6 percent). The construction industry accounted for 20.3 percent of these injuries. Other industry sectors with large shares of fall injuries were retail trade (12.3 percent), transportation and warehousing (10.4 percent), manufacturing (9.3 percent), and health care and social assistance (8.3 percent). Figure 1 shows the number of falls to a lower level that required days away from work, by industry, for 2013.

Some of these industry sectors have high numbers of fall injuries because of their size. Manufacturing (3.7 cases per 10,000 full-time workers) and health care and social assistance (2.9) had lower rates of falls to a lower level than the private industry average (5.1). Retail trade (5.1) had approximately the same rate as all private industry. Both construction (18.0) and transportation and warehousing (12.1) had higher rates than the private industry average, in addition to having large numbers of cases.

Agriculture, forestry, fishing, and hunting, while accounting only for 4.2 percent of the fall injuries, had a rate of 20.3 cases per 10,000 full-time workers. This rate was substantially higher than the private industry average. Within the agriculture industry, fruit and tree nut farming stands out, with 530 cases and a rate of 36.9 per 10,000 full-time workers.

In the fruit and tree nut farming industry, among workers injured by falls to a lower level and requiring days away from work,

- 45.3 percent had less than 3 months of service with their employer;
- 77.4 percent were men and 20.8 percent were women;
- 75.5 percent were Hispanic or Latino, and in another 20.8 percent of the cases race or ethnic origin was not reported;
- 81.1 percent fell from ladders; and

- 41.5 percent of the injuries were sprains, strains, or tears.

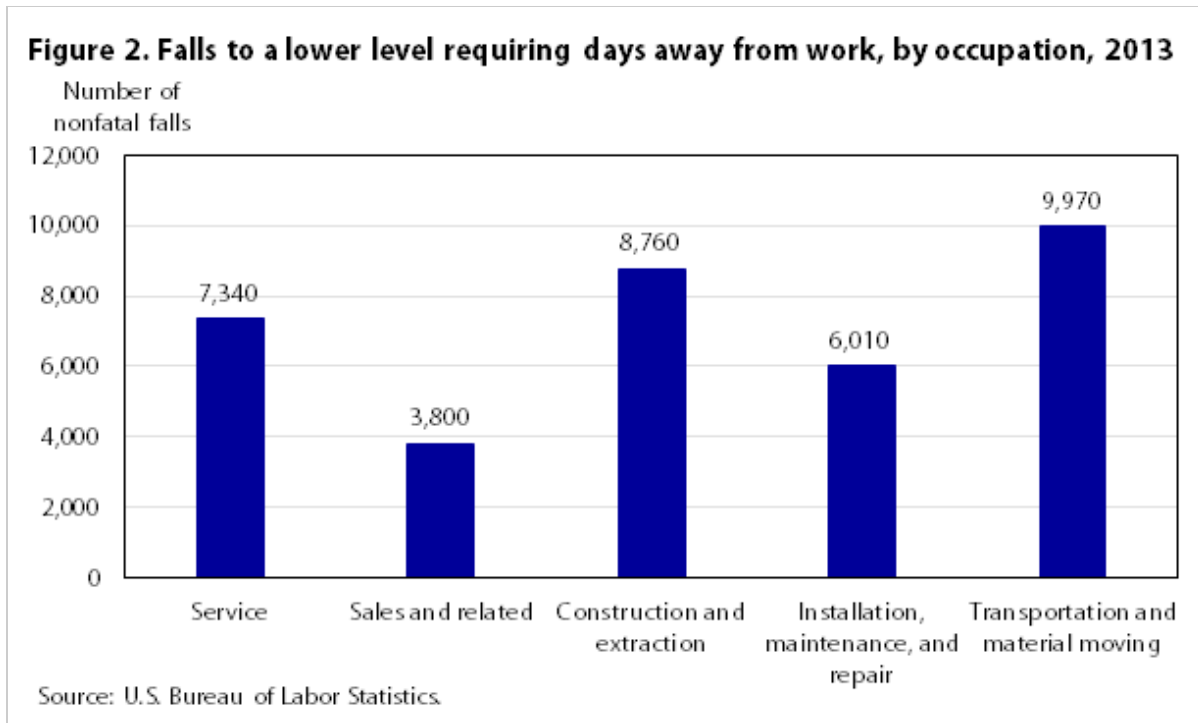
Roofing contractors (NAICS code 23816) have had fall injury rates well above the national average for each of the last 3 years—39.2 in 2013, 50.7 in 2012, and 81.1 in 2011. Key findings for the workers in this industry for days-away-from-work fall injuries are that

- 100 percent were men;
- 51.9 percent were White and 28.8 percent were Hispanic or Latino;
- 48.1 percent of the cases required 31 or more days away from work;
- the median number of days away from work was 26;
- 55.8 percent fell from roofs and 19.2 percent fell from ladders; and
- 51.9 percent of the injuries were fractures.

Another industry with high fall injury rates over the last 3 years is truck transportation (NAICS 484). Workers in this industry had 19.9 fall injuries per 10,000 full-time workers in 2013. Among truck transportation workers,

- 95.5 percent were men;
- 36.6 percent were ages 55 to 64, and 39.7 percent had more than 5 years of service with their employer;
- injuries required a median 30 days away from work;
- in 97.6 percent of the cases, the fall height was either unspecified or less than 6 feet;
- in 53.4 percent of the cases, the source of injury was “trucks—motorized freight hauling and utility”; in 29.5 percent, the source was “floors—walkways—ground surfaces”; and
- in 27.1 percent of the cases, “soreness, pain, hurt—nonspecified” was the nature of the injury. Other frequent natures of injury were sprains, strains, and tears (25.0 percent) and fractures (19.5 percent).

Nonfatal injuries by worker and case characteristics



The majority of the workers who missed days of work because of fall injuries were men, while 27.2 percent were women. In 21.2 percent of the cases, the worker's occupation group was transportation and material moving occupations, and in another 18.6 percent, the workers were employed in construction and extraction occupations. (See figure 2.) In 42.9 percent of the cases, the worker was White. Hispanics represented 18.5 percent of the cases, higher than their share of all private industry injuries and illnesses with days away from work (13.6 percent). In 31.2 percent of the cases, race or ethnic origin was not reported.

Among all private industry fall injuries, in 26.4 percent of the cases the injuries were sprains, strains, and tears, 24.6 percent were fractures, and in 18.7 percent of the cases the nature of the injury was soreness or pain. Approximately three-quarters (76.7 percent) of the falls to a lower level were categorized as event code 433, "other fall to lower level"; 10.2 percent were "fall from collapsing structure or equipment"; and 9.4 percent were "fall to lower level, unspecified." Within "other fall to lower level," when the height of the fall was unspecified or less than 6 feet, there were more sprains, strains, and tears than fractures. From a fall height of 6 to 10 feet and fall height of 11 to 15 feet, there were approximately 5 times as many fractures as sprains, strains, and tears. There are relatively few nonfatal injuries from falls over 15 feet. Much of the data for these categories are not publishable.

In 13.1 percent of the fall-injury cases, the part of body affected was the back. Another 10.1 percent were knee injuries, and 9.4 percent affected the ankle. Floors, walkways, and ground surfaces were the sources of injury in 35.4 percent of the cases, while ladders were the source in 32.5 percent of the cases.

Fatal occupational injuries

The CFOI compiles yearly counts of all fatal work-related injuries in the United States. The scope of the CFOI includes wage and salary workers in private industry, self-employed workers, and government workers at the federal, state, and local levels. The CFOI publishes counts of fatal work injuries at the national level; for each state; for the District of Columbia, Guam, Puerto Rico, and the Virgin Islands; and for many metropolitan statistical areas.

Each year, the CFOI publishes a preliminary count of work-related fatal injuries and, later, a revised and final total. Data for 2013 used in this article are revised and final.

In 2013, 595 workers died as a result of falls to a lower level. The vast majority (95.6 percent) were employed in private industry. Self-employed workers accounted for 26.4 percent of the total, a percentage that was higher than their percentage of all fatal work injuries (20.7 percent). The overwhelming majority (98.2 percent) were men. More than half of these workers were non-Hispanic White (63.7 percent), while 27.4 percent were Hispanic. Among all workers who succumbed to a fatal occupational injury, 17.8 percent were Hispanic.

As with the nonfatal fall injuries, the source of injury was often a roof (22.0 percent) or a ladder (21.5 percent). A vehicle was the source of injury in 11.8 percent of the cases, with trucks accounting for 8.1 percent; and scaffolding or staging was the source of another 11.1 percent. Intracranial injuries accounted for 41.0 percent of the fatal fall injuries.

Almost half (48.9 percent, or 291 cases) of the fatal fall injuries occurred in the private construction industry. (See table 3 and figure 3.) Of these cases, 66 occurred in the roofing contractor industry, and another 40 occurred in the residential building construction industry.

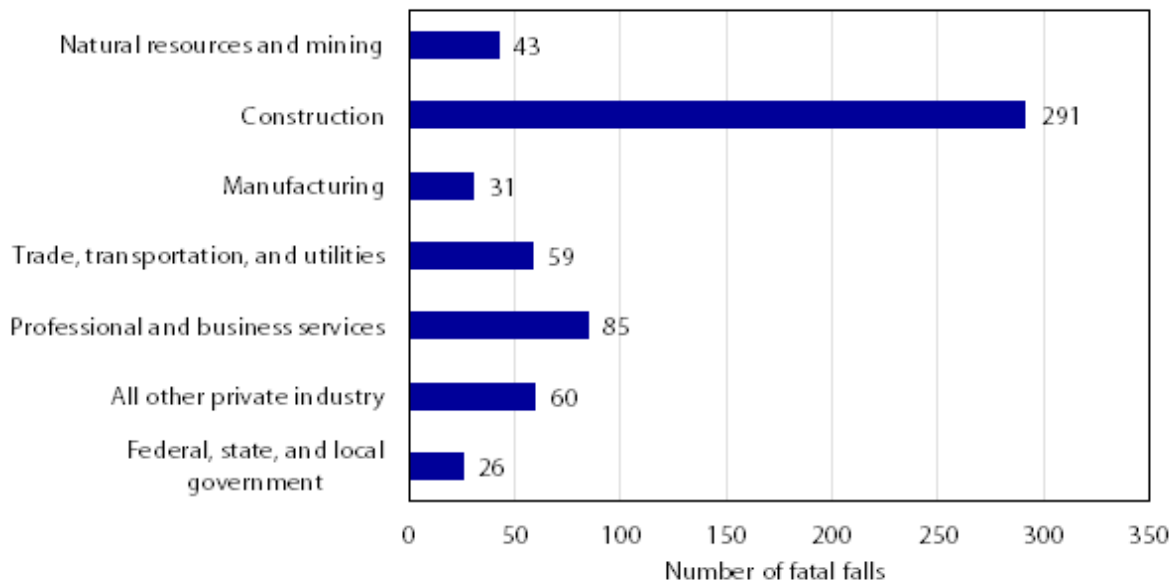
Table 3. Fatal falls to a lower level in the construction industry, 2013

Industry	NAICS code	Fatal falls to a lower level
Construction	23	291
Residential building construction	23611	40
Commercial and institutional building construction	23622	13
Framing contractors	23813	18
Roofing contractors	23816	66
Electrical contractors and other wiring installation contractors	23821	10
Plumbing, heating, and air-conditioning contractors	23822	16
Painting and wall covering contractors	23832	26
Drywall and insulation contractors	23831	12
All other construction industries	—	90

Note: Data are for workers in private industry, government workers, and the self-employed.

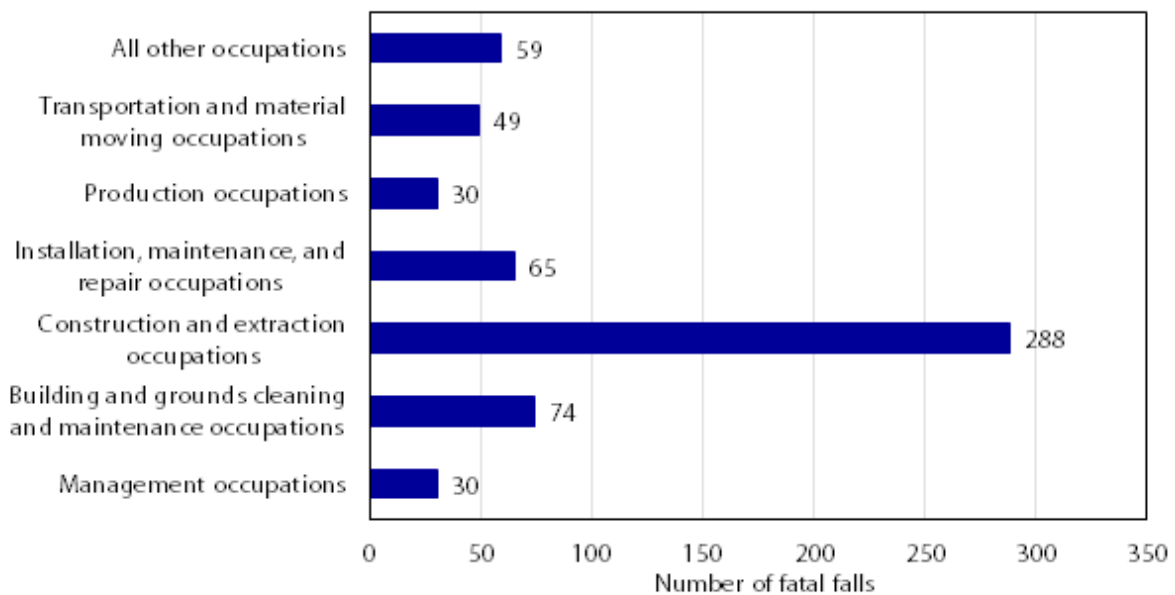
Source: U.S. Bureau of Labor Statistics.

Figure 3. Fatal falls to a lower level, by industry, 2013



Source: U.S. Bureau of Labor Statistics.

Figure 4. Fatal falls to a lower level, by occupation, 2013



Source: U.S. Bureau of Labor Statistics.

In all industries, of the six occupations with the most fatal fall injuries, five were construction and extraction occupations. Nearly half (48.4 percent) of the fatal fall injuries were to workers in this occupation group. (See figure 4.) The occupations with the most fatal fall injuries were roofers (10.8 percent), construction laborers (10.6 percent), carpenters (7.2 percent), and first-line supervisors of construction trades and extraction workers (5.7 percent). Tree trimmers and pruners (4.7 percent) had the most cases among occupations outside of construction.

For fatal falls from a collapsing structure or equipment, 44.4 percent were from heights of 30 feet or more. For fatal falls through a surface or an existing opening, the most common height of the fall was 11 to 15 feet (19.1 percent). Other falls to a lower level accounted for 79.7 percent of all fatal falls to a lower level. Within the fatal falls coded as other falls to a lower level, 15.6 percent were from 11 to 15 feet and 14.1 percent were from more than 30 feet. Falls can be deadly even from shorter distances, as 13.9 percent of the fatal other falls to a lower level were from less than 6 feet.

Conclusion

Falls to a lower level continue to be a major hazard to workers. These falls are the source of 13.0 percent of all fatal occupational injuries; in the construction industry, falls to a lower level account for 34.1 percent of fatal injuries. Falls to a lower level represent 5.1 percent of nonfatal occupational injuries and illnesses in private industry, and these are among the most severe nonfatal cases, as shown by the 21 median days away from work in 2013. New data on the height of falls can help to quantify the increased risks of severe injury and death due to falling to a lower level from a height.

SUGGESTED CITATION

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NOTES

¹ *Fall protection in construction*, OSHA 3146-05R 2015 (U.S. Department of Labor, Occupational Safety and Health Administration), <https://www.osha.gov/Publications/OSHA3146.pdf>.

² Data on nonfatal injuries and illnesses are from the Survey of Occupational Injuries and Illnesses (SOII) program, which collects data from a sample of business establishments in the United States; see "Injuries, illnesses, and fatalities" (U.S. Bureau of Labor Statistics), <https://www.bls.gov/iif/home.htm>.

³ Data on fatal injuries are from "Census of Fatal Occupational Injuries (CFOI)," (U.S. Bureau of Labor Statistics), <https://www.bls.gov/iif/oshcfoi1.htm>. Fatal injuries in this article are based on revised counts for 2013. For more information on both the CFOI and SOII programs, see "Occupational safety and health statistics," *BLS handbook of methods*, chapter 9 (U.S. Bureau of Labor Statistics), <https://www.bls.gov/opub/hom/pdf/homch9.pdf>. The Injuries, Illnesses, and Fatalities Program uses the Occupational Injury and Illness Classification System (OIICS) to define event or exposure, nature, part of body, and source; see "Injuries, illnesses, and fatalities," *Occupational Injury and Illness Classification manual* (U.S. Bureau of Labor Statistics), <https://www.bls.gov/iif/oshoiics.htm>. Occupation is defined with the use of the Standard Occupational Classification (SOC) system; see Standard Occupational Classification (U.S. Bureau of Labor Statistics), <https://www.bls.gov/soc/home.htm>. Industry is defined in accordance with the North American Industrial Classification System (NAICS); see "North American Industry Classification System (NAICS) at BLS" (U.S. Bureau of Labor Statistics), <https://www.bls.gov/bls/naics.htm>.

⁴ From 1992 to 2010, the OIICS divided falls to lower level into several subcategories that describe what the worker fell from—for example, fall from ladder or fall from roof. If, for example, a worker fell 10 feet from a ladder onto the floor, in the 1992–2010 coding system the event would be "fall from ladder" and the primary source would be the ground. The height of the fall was not captured. In the coding system used since 2011, the event would be "other fall to lower level 6 to 10 feet" and the primary source would be the ladder. For the classification system used from 1992 to 2010, see *Occupational Injury and Illness Classification manual* (U.S. Bureau of Labor Statistics, September 2007), https://www.bls.gov/iif/oiics_manual_2007.pdf.

5 “Occupational injuries and illnesses: a pilot study of job-transfer or work-restriction cases, 2011–2013,” report 1056 (U.S. Bureau of Labor Statistics, July 2015), <https://www.bls.gov/opub/reports/job-transfer-or-work-restriction/archive/a-pilot-study-of-job-transfer-or-work-restriction-cases-2011-2013.pdf>.

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Poor is poor and middle is middle, and never the twain shall go any higher

Brian I. Baker

According to the World Bank, the percentage of people living in absolute poverty in the developing world declined from 47 percent in 1990 to 21 percent in 2010 and was projected to drop to 13 percent by 2015. (“World development indicators,” October 2015, table 2.8.2.) Fueling this downturn in poverty was global economic growth, not least in regions that had seen little of it before 1990: Africa, south and east Asia, but also eastern Europe, and Latin America. A list of countries in these regions that saw at least a reasonable amount of economic growth from 1990 to 2010 contains some whose per-capita income grew faster than that of the United States over the period—the Asian “tigers” of Hong Kong, Singapore, South Korea, and Taiwan—as well as some whose income grew in absolute terms, but not faster than U.S. per-capita income: the Latin American countries of Brazil, Ecuador, Guatemala, and Mexico; the African country of Mozambique; and the Asian countries of Bangladesh and Nepal. In “[Relative income traps](#)” (Federal Reserve Bank of St. Louis *Review*, First Quarter 2016), authors Maria A. Arias and Yi Wen tell us that the latter seven countries, plus a large number of others, are in what they call a “relative income trap”: a situation “in which levels relative to the United States remain constantly low with no clear sign of convergence.” Brazil, Ecuador, Guatemala, and Mexico are in a middle-income trap, with per-capita income between 10 percent and 40 percent of U.S. income; and Mozambique, Bangladesh, and Nepal are in a poverty, or low-income, trap, with per-capita income at or below 5 percent of U.S. per-capita income. What is worse, all of these countries, say Arias and Wen, are highly likely to remain trapped at that level, if past experience is any indication.

To investigate the factors contributing to relative income traps, the authors present a model relating countries’ average economic growth during several periods of growth to their gross volume of trade, the contemporaneous exchange rate, investment, government expenditures, inflation, and market orientation. They find that strong economic growth relative to the United States is correlated with a country’s volume of trade, investment, and market orientation, but not with the exchange rate or government expenditures. Then, using the correlates of strong economic growth relative to the United States, Arias and Wen set up a probability matrix to calculate the likelihood of a country’s having a relative income in income range j today, given that the country had a relative income in income range i during the previous period. In other words, the matrix gives the probability of a country’s transitioning from income range i to income range j . (If $i < j$, the matrix gives the probability of a country’s escaping a low- or middle-income trap to a higher income level.) To determine whether a particular country’s escape is “permanent,” the authors apply the matrix to three distinct intervals: spanning 10 years, 20 years, and 30–61 years (the latter depending on the number of years data were available, for each country). Their findings are, in general, no cause for optimism.

First, the probability of a low-income country's remaining that way is a very high 94 percent after 10 years, a still very high 90 percent after 20 years, and a continuingly high 80 percent after 30–61 years—ergo the name “poverty trap.” Similarly, the probability of a middle-income country's remaining that way is a very high 89 percent after 10 years, a quite high 79 percent after 20 years, and a still relatively high 64 percent after 30–61 years—ergo the name “middle-income trap.” (Worse, the middle-income percentages include a regression to a poverty trap for 9 percent of the countries after 10 years, 14 percent after 20 years, and 17 percent after 30–61 years.)

So, what is the prognosis for the future? Not very encouraging, to say the least. According to the authors, “even the poorest economies continue to grow at some positive rate each year; but unless lower-income economies persistently grow at a rate faster than the developed economies” (an almost impossible task, according to Arias and Wen), “they will not be able to catch up.” The lone ray of hope they offer comes out of the findings from the model they present: the correlation between strong economic growth relative to the United States, on the one hand, and a country's volume of trade, investment, and market orientation, on the other, suggests that “those countries that can find ways to grow their manufacturing sector through continuous market creation, investment, and exports [will be] more capable of achieving technological and income convergence to the technology frontier” and thus more likely to escape the poverty or middle income trap in which they currently find themselves.

Putting violence in perspective: how safe are America's educators in the workplace?

As safety in schools continues to be in the national spotlight, the need to identify circumstances that jeopardize the educators' safety becomes pressing. Violent events capture our attention; however, do violent events compose the majority of educator workplace injuries and illnesses? If not, then what are the events and sources under which educators are hurt or killed on the job? To address these questions, we compare workplace violence experienced by educators with their overall workplace injuries and illnesses. Fatal injury data were taken from the Census of Fatal Occupational Injuries and nonfatal days-away-from-work data from the Survey of Occupational Injuries and Illnesses. This article also examines differences in educator workplace injuries and illnesses by level of instruction, sector, and gender. From 2011 through 2014, transportation incidents led to the most fatalities among educators—violent events were the second most frequent. In 2014, falls, slips, and trips led to the most nonfatal days-away-from-work cases—violent events were the second most frequent.

Out of the 8.4 million workers employed in the education, training, and library occupations throughout the United States in 2014, 27 died on the job and 36,540 had nonfatal occupational injuries and illnesses that resulted in days away from work.¹ Compared with all workers in the United States, those in the education, training, and library occupations (henceforth referred to as “educators”) were at less risk of both fatal injuries and nonfatal injuries and illnesses.² The fatal injury incidence rate for educators, at 0.4 per 100,000 workers, was significantly lower than the rate for all workers (3.4 per 100,000 workers). Likewise, the nonfatal injury and illness incidence rate for educators for days away from work was 59 cases per 10,000 full-time workers and was almost half the rate for all workers at 107.1 per 10,000 full-time workers. All work injuries and illnesses are unfortunate, but among them, events of violence and other injuries by persons or animals (henceforth referred to as “violent events”) stand out as preventable. Violent events from 2011 through 2014 composed 27 percent (29 deaths) of the fatal injuries of



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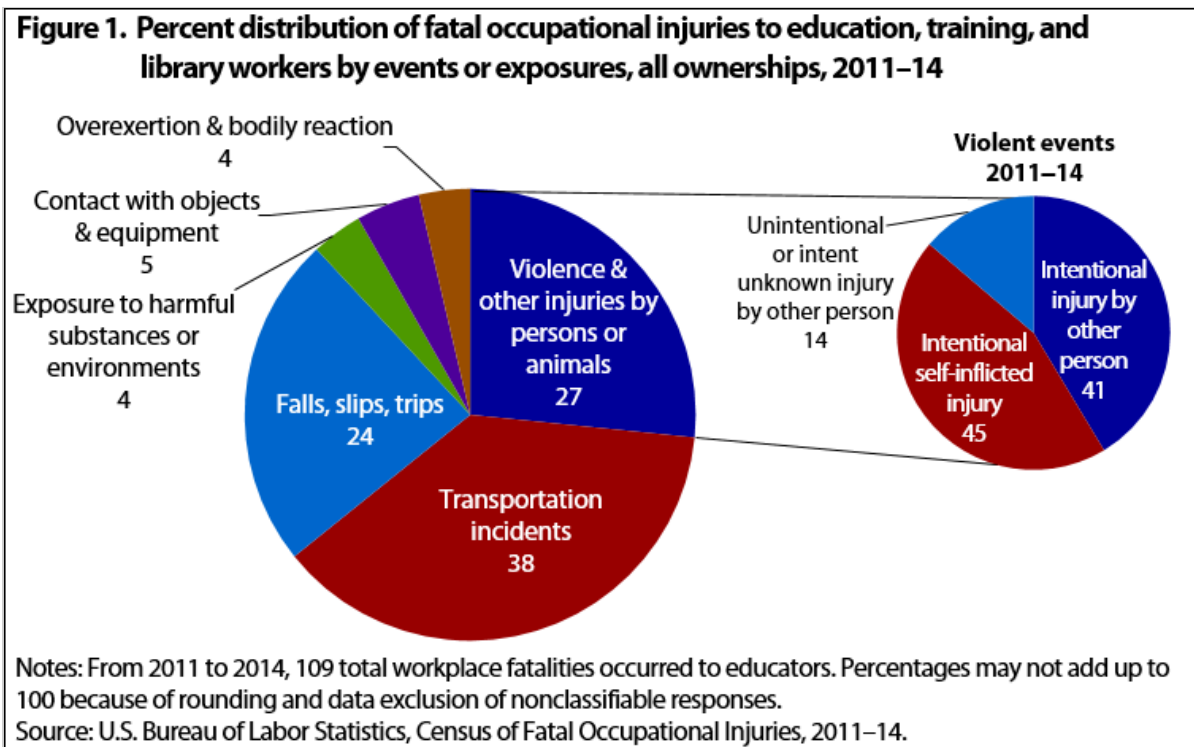
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educators. In 2014, they composed 24 percent of the nonfatal days-away-from-work cases (8,620 cases) that educators experienced. This article explores occupational fatal injuries and nonfatal injuries and illnesses that resulted in days away from work for educators, with a focus on violent events.

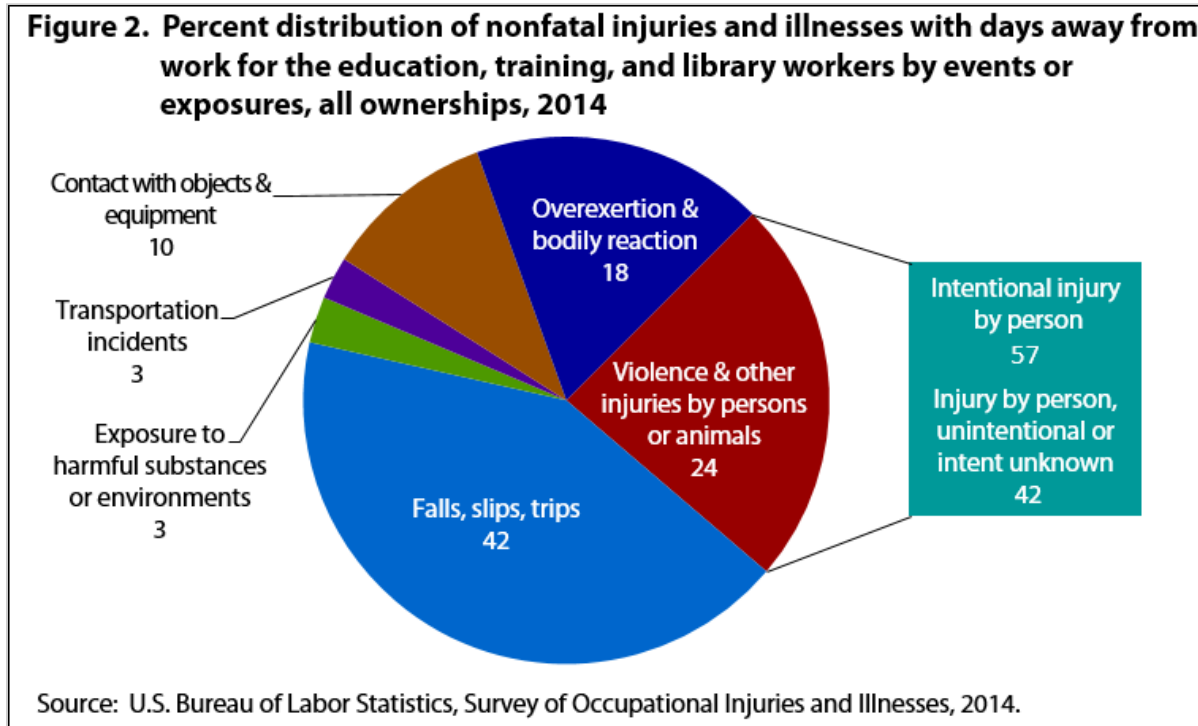
Types of violent events affecting educators

For this article, violent events are considered any event that falls into event category 1 in the Occupational Injury and Illness Classification System 2.01 coding structure.³ This category includes all intentional injuries (homicides and suicides), injuries involving weapons, and injuries from direct physical contact by another person or oneself. From 2011 through 2014, 109 educators were fatally injured on the job.⁴ Violent events accounted for 27 percent of fatal injuries (29 deaths) to educators and were the second most frequent type of fatal incident after transportation incidents (see figure 1). Of the educators who were fatally injured in violent events from 2011 through 2014, 69 percent (20 of the 29) were employed in state or local government.⁵ Of the 29 violent deaths, 25 were reported as intentional injuries by persons (this category includes injuries by other persons and self-inflicted injuries or suicides). Self-inflicted intentional injuries numbered 13 of the 29 violent fatalities (45 percent), and intentional injuries (i.e., homicides) by other person were the second most common fatal violent event, with 12 fatalities. Among the educators who were victims of homicides from 2011 through 2014, eight occurred as intentional shootings by other persons (67 percent). Four cases were classified as “injury by other person—unintentional or intent unknown.” These cases can include accidental shootings or physical contact during activities such as sports or attempts to restrain another person.



Of the 36,540 nonfatal injuries and illnesses that resulted in days away from work reported in 2014 for educators,⁶ nearly a quarter (8,620 cases) were the result of violent events (see figure 2). The share of the number of violent events to all nonfatal days-away-from-work cases was more than three times higher for educators than for all workers in the United States in 2014. Also, the incidence rate of violent events among educators (13.9 per

10,000 full-time workers) was almost twice the incidence rate (6.8) of violent events for all workers in the United States. Compared with major occupation groups with high rates of violent nonfatal events, educators were at low risk. For example, protective service workers (such as police officers or fire fighters) or healthcare support workers (such as home health aides or personal care assistants) had higher rates, at least by a factor of two, of violent events at work than educators (see table 1).



Surpassed only by falls, slips, and trips in number of days-away-from-work cases, violent events were the second most frequent nonfatal event. Violent events were split by intent, with 57 percent (4,910 cases) categorized as intentional injury by person and 42 percent (3,580 cases) categorized as unintentional or intent-unknown injury by person. Three-quarters of violent events to educators occurred among workers in local government with 6,550 cases, followed by 1,930 cases in private industry, and 140 cases in state government. This pattern was similar to both the distribution of total employment by ownership of educators across the United States as well as the distribution of total number of nonfatal cases by ownership involving days away from work in 2014.⁷

Table 1. Nonfatal incidence rate of violence and other injuries by persons or animals involving days away from work, by major occupation groups, all ownerships, 2014

Major occupation groups ⁽¹⁾	Incidence rate for events of violence and other injuries by persons or animals	Total incidence rate
Protective service	68.4	298.7
Healthcare support	37.3	220.6
Community and social service	24.1	94.9
Personal care and service	23.1	110.3
Farming, fishing, and forestry	19.7	149.8
Healthcare practitioners and technical	15.0	103.6
Education, training, and library	13.9	59.0

See footnotes at end of table.

Table 1. Nonfatal incidence rate of violence and other injuries by persons or animals involving days away from work, by major occupation groups, all ownerships, 2014

Major occupation groups ⁽¹⁾	Incidence rate for events of violence and other injuries by persons or animals	Total incidence rate
All workers	6.8	107.1
Arts, design, entertainment, sports, and media	6.7	47.9
Building and grounds cleaning and maintenance	4.4	258.5
Construction and extraction	3.2	189.5
Installation, maintenance, and repair	2.3	202.9
Life, physical, and social science	2.1	37.1
Management	1.9	36.9
Sales and related	1.7	51.8
Food preparation and serving related	1.2	96.9
Office and administrative support	.9	50.4
Production	.7	136.5
Business and financial operations	.5	15.7
Architecture and engineering	.2	18.8
Computer and mathematical	.1	8.3
Legal	(2)	15.5

Notes:

(1) Data on transportation occupations and military-specific occupations are not displayed. Data on the transportation occupations were only available for private industry (i.e., not for all ownerships). The Survey of Occupational Injuries and Illnesses does not collect data on military personnel.

(2) Data did not meet publication guidelines because of rounding and data exclusion of nonclassifiable responses or because data were too small to be displayed.

Note: Major occupations are grouped according to the “2010 Standard Occupational Classification Manual,” Office of Management and Budget. The incidence rates represent the number of injuries and illnesses per 10,000 full-time workers.

Source: U.S. Bureau of Labor Statistics, Survey of Occupational Injuries and Illnesses, 2014.

For educators in 2014, the total days-away-from-work incidence rate per 10,000 full-time workers was statistically the same for those employed in private industry and those employed by local governments (69.3 and 66.3, respectively) (see table 2). However, local government educators experienced a higher rate of violent events than those in the private industry (17.0 and 13.5, respectively).

Table 2. Incidence rates for days-away-from-work cases by selected events or exposures and ownership for education, training, and library occupations, 2014

Characteristic	All educators	Pre-K–12 educators ⁽¹⁾
Total all ownerships		
All events or exposures	59.0	(2)
Violent events or exposures	13.9	—
Local government		
All events or exposures	66.3	49.2
Violent events or exposures	17.0	8.9
Private industry		

See footnotes at end of table.

Table 2. Incidence rates for days-away-from-work cases by selected events or exposures and ownership for education, training, and library occupations, 2014

Characteristic	All educators	Pre-K–12 educators ⁽¹⁾
All events or exposures	69.3	85.8
Violent events or exposures	13.5	12.4
State government		
All events or exposures	16.9	—
Violent events or exposures	2.2	—

Notes:

⁽¹⁾ Pre-K–12 educators represent the minor occupation group "preschool, primary, secondary, and special education school teachers," with code 25-2000 according to the "2010 Standard Occupational Classification Manual," (<https://www.bls.gov/soc/2010/>).

⁽²⁾ The total all ownership rate for pre-K–12 educators is not available for all events or exposures and violent events because the state government rates were not available.

Note: Incidence rates for days-away-from-work cases are calculated per 10,000 full-time workers. Dash indicates data not available.

Source: U.S. Bureau of Labor Statistics, Survey of Occupational Injuries and Illnesses, 2014.

However, this pattern of local government educators having higher rates than those of private industry educators did not hold among preschool, primary, secondary, and special education school teachers (henceforth referred to as "pre-K–12 teachers"). Private industry pre-K–12 teachers had higher rates of both total nonfatal cases and violent events than local government pre-K–12 teachers. In fact, the total nonfatal incidence rate for private pre-K–12 teachers was almost twice that of local government pre-K–12 teachers (85.8 and 49.2 per 10,000 full-time workers, respectively). The rate of violent events for pre-K–12 teachers in the private industry increased from 8.8 per 10,000 full-time workers in 2011 to 12.4 in 2014.

Sources of violent events

The primary source of an occupational injury is the object, substance, person, bodily motion, or exposure that most directly led to, produced, or inflicted the injury or illness. The secondary source of an occupational injury is the object, substance, person, or exposure, other than the primary source, if any, that most actively generated the source or contributed to the injury or illness. When a source is referred to as "primary" or "secondary," it does not indicate the number or rate of cases. It simply indicates the level of importance an object, a piece or equipment, or machinery had in an event or exposure leading to a fatal or nonfatal injury or illness.

In cases of suicide, workers are considered the primary source and the means that they used to kill themselves is considered the secondary source.⁸ In addition, in fatal violent events toward another person, the assailant is considered the primary source. The object or means used to kill the other person is considered the secondary source. Therefore, in fatal violent events overall, the fatally injured worker was the primary source of all 13 suicides from 2011 to 2014. Relatives or domestic partners were the primary source of 4 of the 12 homicides. For all workers in the United States, in 2014, relatives or domestic partners were the primary source of 32 percent of homicides for women and 2 percent for men.⁹ Students were the primary source of three of the homicides of educators. In 8 of the 12 homicides, a firearm was the secondary source. The most frequently used firearm was

categorized as a pistol, handgun, or revolver, which was used in five of the eight cases in which a firearm was the secondary source.

Students were the primary source of injury or illness in 92 percent (7,900 cases) of the 8,620 nonfatal violent events that educators experienced in 2014. This percentage of violent events involving students increased 23 percent since 2011 from 6,410 cases. Although students were the primary source of the majority of violent events to educators, students were the primary source of only 26 percent (9,580 cases) of the total days-away-from-work cases on the job in 2014.

In 2014, students were the source of nonfatal injury or illness in nearly twice as many intentional violent events by persons experienced by educators as they were for unintentional or intent-unknown violent events. Although students were the primary source in more intentional violent events, the median days away from work due to unintentional or intent-unknown events (7 median days away) was 4 days higher than the median for intentional cases. Hitting, kicking, beating, and shoving accounted for 93 percent (4,360 cases) of intentional violent nonfatal events by persons and kept educators away from work for a median of 3 days to recuperate. Nearly half of the educators injured unintentionally or with unknown intent (1,500 cases) were injured during physical contact while restraining or subduing a student. Injuries by physical contact during horseplay with students numbered 200 cases.

Nonviolent events and their sources

Transportation incidents were the most common event or exposure that resulted in fatal injuries among educators from 2011 through 2014.¹⁰ They represented 38 percent of all fatal injuries (41 deaths) to educators. Of the transportation incidents, roadway incidents involving motorized land vehicles accounted for 37 percent of fatal injuries for educators (15 deaths). Examples of educators fatally injured in roadway incidents could include those which occur when educators supervise students on a school bus, a school-sponsored field trip, or other work-related trip. Another 29 percent (12 deaths) of the transportation incidents that resulted in fatal injuries to educators were aircraft incidents. Of the 12 aircraft transportation incidents resulting in fatal injuries to educators, 8 involved skydiving instructors. Falls, slips, and trips were the third most common fatal event or exposure from 2011 through 2014 (with violent events as the second most frequent, as discussed earlier). They composed 24 percent of all educator fatalities (26 deaths). Approximately, two-thirds of the fatal falls, slips, and trips were falls on the same level (16 deaths), and one-third were falls to a lower level (10 deaths).

Since transportation incidents and falls, slips, and trips were the two most common fatal nonviolent injury events for educators, vehicles along with floors, walkways, and ground surfaces were consequently their most common primary sources. Among vehicles, passenger vehicles were the source of 17 cases or 41 percent of fatal transportation incidents. Floors, walkways, and ground surfaces were the sources reported for 20 educator fatalities (18 percent) from 2011 through 2014.

In 2014, falls, slips, and trips were the most common nonfatal event or exposure for all educators whose injuries or illnesses resulted in days away from work (15,360 cases). Educators were at a higher risk of nonfatal falls, slips, and trips (24.8 per 10,000 full-time workers) on the job than they were of violent events (13.9 per 10,000 full-time workers). Those who did fall, slip, or trip required a median of 6 days away from work to recuperate—1 day more than those who experienced violent events. Falls on the same level far outnumbered violent events and accounted for 31 percent of the educators' total nonfatal days-away-from-work injuries and illnesses (11,280 cases). Floors, walkways, and ground surfaces accounted for 88 percent (9,960 cases) of the sources of falls on the same level.

Ice, sleet, and snow (1,400 cases) and furniture and fixtures (1,040 cases) were two notable factors that contributed to persons falling on the same level while walking on floors, walkways, and ground surfaces.

Following violent events in 2014, cases of overexertion and bodily reaction were the next most common nonfatal event or exposure (6,540 cases).¹¹ These types of events or exposures resulted after low- or no-impact physical effort in a single episode or repetitive motion over time. Educators were out for similar periods for these types of cases as they were for violent events. Specifically, everyday work activities such as bending, crawling, reaching, twisting, climbing, or stepping led to a median of 5 days away from work, the same median as that for violent events. Educators with less than 1 year length of service at an establishment had substantially higher medians (40 median days away) because of these everyday types of motions than those with 1 year or more length of service (5 median days away).

Contact with objects and equipment (3,810 cases), exposure to harmful substances or environments (1,030 cases), and transportation incidents (950 cases) together composed 16 percent of nonfatal injuries and illnesses to educators. Educators injured from contact with objects and equipment required 3 median days away from work to recuperate, whereas those injured either from exposure to harmful substances or environment or from transportation incidents required only 2 median days away. Approximately 930 educators were struck by recreation and athletic equipment, and another 950 were injured in transportation incidents involving vehicles. Of those who were exposed to harmful substances or environments, two out of five were exposed to bacteria and general chemical products (410 cases).

Detailed findings by level of instruction

Pre-K–12 teachers accounted for 36 percent (39 of 109 deaths) of all fatally injured educators from 2011 through 2014 across all ownerships.¹² Of all educators, pre-K–12 teachers also suffered the highest number of fatal violent events during this period and were the victims in 12 of the 29 fatal violent events (41 percent). Postsecondary teachers, the second most common occupation, accounted for 22 percent of fatalities (24 deaths) across all ownerships and were the victim in 34 percent of all violent events (10 of the 29 events). Half of the pre-K–12 teachers who were fatally injured in a violent event were killed in a homicide (6 deaths). Whereas, of the postsecondary teachers fatally injured in violent events, 70 percent committed suicide (7 deaths).

Self-enrichment education teachers had the most fatal injuries among educators in private industry (21 of 48 deaths). Self-enrichment teachers instruct courses other than those which normally lead to an occupational objective or degree and can include nonvocational and nonacademic subjects. Examples of these subjects include skydiving instruction and firearm instruction, among others. Elementary and middle school teachers had the most fatal injuries among educators in local government with 15 of 42 (36 percent) fatal injuries.

Teacher assistants had the highest number of nonfatal injuries and illnesses that resulted in days away from work in 2014 among educators (12,620 cases) for all ownerships, state government as well as local government. They required a median of 6 days away from work to recuperate from injuries and illnesses. For private industry educators in 2014, preschool teachers, except special education, had the highest number of days-away-from-work cases at 3,140—280 of those were due to violent events. They required 12 median days away from work to recuperate from a violent event, 7 more than the median for all their events. Teacher assistants accounted for 56 percent (4,830 cases) of educators who experienced violent events on the job in 2014 and required 3 median days

away to recuperate after a violent event. From 2011 to 2014, teacher assistants accounted for approximately 33 percent of total days-away-from-work cases and 45 percent of nonfatal violent event cases.

Following teacher assistants, those employed as elementary and middle school teachers experienced the second most frequent number of violent events by any detailed educator occupation (1,820 cases) and required 7 median days away from work to recuperate after a violent event.

The detailed educator occupation with the longest median days away from work due to violent events (52 median days away from work, 290 cases) was the secondary school teachers, except special education and career technical education. Special education teachers in middle schools followed them at 26 median days away from work (50 cases).

Distribution of cases by gender

From 2011 through 2014, women composed 42 percent of fatal injuries within the educator occupation and 8 percent of all workers fatally injured on the job across the United States. In 2014, nearly 75 percent of the educators in the United States were women and women represented 48 percent of educators' workplace fatalities (13 deaths).¹³ From 2011 through 2014, women were the victims in 13 of 29 fatal violent events (45 percent) and men the victims in 16 of 29 (55 percent) fatal violent events.

The share of days-away-from-work cases for women in 2014 was similar to their share of total employment. Among educators, women experienced 87 percent of nonfatal violent events and 85 percent of all days-away-from-work injuries. Although men had fewer cases, they required nearly twice the recuperation time after violent events (9 median days away from work) and 1 more median day for all injuries (6 days away from work). Women took 5 median days away from work for both total injuries and illnesses and violent events. Using the median days away as a proxy for a measure of severity indicates that when male educators were hurt or injured during a violent event on the job, they sustained more severe injuries and thus required more days away from work. For example, in cases in which female educators required 3 median days away from work (4,140 cases) to recuperate because of hitting, kicking, beating, and shoving by students, male educators who experienced these same events (440 cases) required a median of 8 days away from work.

Summary of findings

Violent events were not the leading fatal event category under which educators were reported as killed on the job. From 2011 through 2014, more educators died in transportation incidents than in any other event. Hence, vehicles were the leading source of educator fatalities on the job from 2011 through 2014 (38 percent) (see table 3). The most frequent type of violent event was suicides.

Table 3. Percentages of total fatal injuries (109) and total nonfatal cases (142,600) involving days away from work for education, training, and library occupations, by selected primary sources, 2011–14

Primary source ⁽¹⁾	Fatal injuries	Nonfatal injuries or illnesses with days away from work
Total percentage	100	100
Vehicles	38	3

See footnotes at end of table.

Table 3. Percentages of total fatal injuries (109) and total nonfatal cases (142,600) involving days away from work for education, training, and library occupations, by selected primary sources, 2011–14

Primary source ⁽¹⁾	Fatal injuries	Nonfatal injuries or illnesses with days away from work
Floors, walkways, ground surfaces	18	33
Person—injured or ill worker	15	15
Student	5	25
All other sources	25	24

Notes:

⁽¹⁾ Data shown in columns correspond to the “Occupational Injury and Illness Classification Manual” 2.01 source codes in which vehicles = 8; floors, walkways, and ground surfaces = 66; person—injured or ill worker = 56; and student = 573.

Sources: U.S. Bureau of Labor Statistics, Census of Fatal Occupational Injuries (fatal injuries), and Survey of Occupational Injuries and Illnesses (nonfatal injuries and illnesses).

Violent events were also not the leading nonfatal event category under which educators required days away from work. The leading event for nonfatal days-away-from-work cases from 2011 through 2014 was falls, slips, and trips (43 percent). Hence, floors, walkways, and ground surfaces were the primary sources of nonfatal injuries and illnesses that resulted in educators taking days away from work (see table 3).

SUGGESTED CITATION

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NOTES

¹ Total employment data on educators were taken from the BLS Occupational Employment Statistics program, May 2014, <https://www.bls.gov/oes/tables.htm>. Educators represent all occupational groups under the education, training, and library occupations 25-0000 category that is based on the “2010 Standard Occupational Classification Manual,” <https://www.bls.gov/soc/2010/>.

² Data on fatalities were taken from the Census of Fatal Occupational Injuries (CFOI). Fatality data for 2014 are based on final counts released April 21, 2016. Data on nonfatal occupational injuries and illnesses involving days away from work were taken from the Survey of Occupational Injuries and Illnesses (SOII). BLS conducts both the CFOI and SOII. For a detailed explanation of the scopes of CFOI and SOII, see the *BLS Handbook of Methods*, chapter 9, “Occupational safety and health statistics” (U.S. Bureau of Labor Statistics), <https://www.bls.gov/opub/hom/pdf/homch9.pdf>.

³ Events discussed in this article are defined under the Occupational Injury and Illness Classification System 2.01 structure as events or exposures at https://www.bls.gov/iif/oiics_manual_2010.pdf. They describe the manner in which the injury or illness was produced or inflicted by the source of injury or illness.

⁴ Fatal injury data focused on the years 2011 through 2014, whereas nonfatal days-away-from-work data focused on 2014. The average number of fatalities was 27 annually. As a result, fatal injury data from 2011 through 2014 are presented as an aggregate to avoid issues of data suppression. The nonfatal occupational estimates mentioned throughout this article are for 2014, unless otherwise mentioned.

⁵ Occupational injuries and illnesses are presented by ownership: private industry, local government, and state government. Cities, parishes, etc., are classified as local government. All ownerships are the sum of private, local, and state governments. Educators of

all levels of instruction can work in each sector. The Census of Fatal Occupational Injuries includes federal and self-employed workers, whereas federal and self-employed workers are not included in the Survey of Occupational Injuries and Illnesses.

6 Days away from work are a type of nonfatal occupational injury or illness wherein the worker is out of work a minimum of 1 full day or more after the event or exposure occurs. These cases include workers who return to their regular job duties or are put on restricted work once they return.

7 Within the education, training, and library occupations, the local government employed 65 percent (5,470,880 workers), private industry employed 24 percent (2,052,620 workers), and the state employed 10 percent (880,770 workers) of educators. For more information, see BLS Occupational Employment Statistics program, May 2014, at <https://www.bls.gov/oes/tables.htm>.

8 Of the 16 fatalities in which the educator was the primary source, 13 were suicides and 3 were from bodily motion, specifically as events of overexertion and bodily reaction.

9 See BLS 2014 chart package of the “Census of Fatal Occupational Injuries—current and revised data,” charts titled “Fatal work injuries and hours worked by gender of worker, 2014,” p. 8; “Distribution of fatal injury events by gender of worker, 2014,” p. 9; and “Work related homicides by gender of decedent and assailant type, 2014,” p. 10, <https://www.bls.gov/iif/oshwc/cfoi/cfch0013.pdf>.

10 Fatal injuries that occurred during a person’s normal commute to or from work are out of scope, unless the incident occurred on the employer’s premises.

11 In 2014, the educator was the primary source of 5,920 nonfatal days-away-from-work cases—58 percent involved events of overexertion and bodily reaction (3,450 cases) and 38 percent involved falls, slips, and trips (2,230 cases).

12 Detailed occupations mentioned in this section are from the “2010 Standard Occupational Classification Manual,” as follows: preschool, primary, secondary, and special education school teachers = 25-2000; postsecondary teachers = 25-1000; self-enrichment education teachers = 25-3020; elementary and middle school teachers = 25-2020; teacher assistants = 25-9041; secondary school teachers, except special education and career technical education = 25-2031; and special education teachers, middle school = 25-3053. Fatal injury rates for educators are not available past the two-digit detail level for occupations. Selected rate categories for rates that the Census of Fatal Occupational Injuries (CFOI) produced had 15 or more reported fatal work injuries in 2014 and 40 million or more work hours (20,000 full-time equivalent employees). Rates may not be produced if they do not meet this threshold in 2014. Rates that the CFOI produced can be found at <https://www.bls.gov/iif/oshcfoi1.htm>.

13 Current Population Survey, “Employed persons by detailed occupation, sex, race, and Hispanic or Latino ethnicity” (U.S. Bureau of Labor Statistics, 2014), p. 3, <https://www.bls.gov/cps/aa2014/cpsaat11.htm>.

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Current Employment Statistics survey: 100 years of employment, hours, and earnings

To help mark the Monthly Labor Review's centennial, the editors invited several producers and users of BLS data to take a look back at the last 100 years. For the last 100 years, the Current Employment Statistics (CES) program has produced and published critical economic data on employment and earnings. The scope of industries covered by CES has evolved over time to include the majority of the nonfarm economy, and the types of data have expanded to include, for example, average weekly hours and women workers. Over the century, changes in employment trends have been shaped by numerous forces, whether industry specific or broader in scope. CES data capture these trends and allow for an in-depth analysis of the changing employment structure of the national economy over the last 100 years.

Each month, the U.S. Bureau of Labor Statistics (BLS) Current Employment Statistics (CES) program surveys approximately 146,000 businesses and government agencies, which represent approximately 623,000 worksites in the United States. The data collected allow CES to produce detailed industry estimates of employment, hours, and earnings on the basis of payroll records of nonfarm business establishments. These data, along with data from the Current Population Survey, serve as the first economic indicator of current employment trends each month and are used to help gauge the overall health of the U.S. economy. In addition, average weekly hours series may reflect short-term fluctuations in labor demand and typically lead changes in employment. The average hourly earnings series helps determine earnings trends and may signal potential wage-push inflation.

The CES program dates back to October 1915, when a small sample of manufacturers was asked to provide total employment and payroll data. That year, their employees earned an average \$10.28 per week,¹ compared with \$832.42 per week for employees of all manufacturing industries 100 years later.



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In 1919, BLS first published monthly data on employment and earnings for production workers in manufacturing (monthly average weekly hours data for these workers were added a few years later). That same year, CES began publishing annual employment data for various industries, including detailed industries in the goods-producing sector and in the service-providing sector, the latter of which included wholesale and retail trade, transportation and public utilities, and government. (See table 1.) Nonfarm payroll employment rose from 27.1 million in 1919 to 143.1 million in December 2015, with growth averaging 1.7 percent per year. However, annual job growth has fluctuated over the period. For example, employment fell by a series low of 11.3 percent in 1932 and rose by 12.9 percent in 1941, a series high.

Table 1. Annual average employment, not seasonally adjusted, 1919

Industry	Employment level (in thousands)
Total nonfarm	27,078
Total private	24,402
Goods-producing	12,828
Mining	1,133
Construction	1,036
Manufacturing	10,659
Service-providing	14,250
Private service-providing	11,574
Transportation and public utilities	3,711
Wholesale and retail trade	4,514
Government	2,676

Source: Current Employment Statistics, U.S. Bureau of Labor Statistics.

Since 1939, the CES program has published monthly data for total nonfarm employment and employment in selected major industries on the basis of the Standard Industrial Classification (SIC) system for all major industry sectors. Over time, more industry detail was added to SIC. In 2003, CES estimates were converted to the North American Industry Classification System (NAICS), which divided the industry structure into additional sectors.² Where possible, some CES employment series, including those for major industry sectors, have been reconstructed as far back as 1939. However, all national CES employment series first published under NAICS have series start dates of no later than 1990.

The analysis in this article focuses on longrun employment trends dating as far back as 1939; for employment series with later start dates, shorter periods of time are analyzed. Changes in employment for major industry sectors from January 1939 through December 2015 are discussed, and major historical events or other dynamics within the economy causing changes in employment trends are highlighted. Where more detailed industries have substantially contributed to the changes observed at the sector level, those industries are also discussed.

Overall employment trends

Since January 1939, job growth in the United States has averaged 2.1 percent per year. (See table 2.) Private service-providing industries have experienced relatively consistent growth and increased their share of

employment from 50 percent to 71 percent through December 2015. By contrast, the share of total employment in goods-producing industries fell from 37 percent to 14 percent over the same period.

Table 2. Employment change as a percentage of total nonfarm (TNF) change by industry, seasonally adjusted, 1939–2015

Total nonfarm data	1939–45	1945–72	1972–79	1979–2001	2001–15	1939–2015	
Employment level change (in thousands)	9,189	36,158	15,403	40,332	12,141	113,223	
Annualized percent change	3.9	2.5	2.7	1.7	0.6	2.1	
Industry data (industry employment change as a percent of TNF employment change)	1939–45	1945–72	1972–79	1979–2001	2001–15	1939–2015	
						Employment level change (in thousands)	Percent of TNF change
Total private	80	78	84	87	94	95,171	84
Goods-producing	40	22	14	-5	-28	8,580	8
Mining and logging	0	-1	2	-1	1	-121	0
Construction	2	7	4	5	-2	5,458	5
Manufacturing	38	16	7	-9	-28	3,243	3
Private service-providing	40	56	70	92	122	86,591	76
Trade, transportation, and utilities ⁽¹⁾	18	19	22	18	12	20,478	18
Wholesale trade	3	5	6	3	2	4,418	4
Retail trade	7	12	13	12	6	12,654	11
Information	5	2	2	3	-6	1,651	1
Financial activities	1	6	7	7	2	6,819	6
Professional and business services	6	9	12	21	32	18,047	16
Private education and health care	4	9	13	23	52	20,997	19
Leisure and hospitality	4	8	9	13	28	13,482	12
Other services	2	3	5	7	3	5,117	5
Government	20	22	16	13	6	18,052	16

Notes:

⁽¹⁾ Includes additional series not shown separately.

Note: Calculations for 1939 use January data. Calculations for all other years use December data.

Source: Current Employment Statistics, U.S. Bureau of Labor Statistics.

During the World War II (WWII) era, employment rose rapidly January 1939 through November 1943 (+12.9 million), then fell by 3.7 million through December 1945. On net, employment increased by an annualized rate of 3.9 percent during that time span. Job gains were concentrated in manufacturing and government, which accounted for 38 and 20 percent, respectively, of net employment growth.

From 1948 through 1972, labor productivity (output per hour of work) rose by an average 2.8 percent per year and nonfarm employment grew at an annualized rate of 2.5 percent.³ From December 1945 through December 1972, manufacturing fell from 38 percent to 16 percent of job growth, while private service-providing industries expanded from 40 percent to 56 percent of overall growth.

Over the next 7 years, through December 1979, employment grew at a 2.7-percent annualized rate. During this period, labor productivity increased by an average of 1.5 percent per year and real gross domestic product (GDP) advanced at a 3.1-percent annualized rate. Manufacturing employment reached an alltime peak and accounted for only 7 percent of all jobs added. Government reduced its share of net employment growth during this period, while private service-providing industries added relatively more jobs. Each of three service industries—retail trade, professional and business services, and private education and health care—accounted for more than 10 percent of net employment gains during this period.

From 1979 to 2001, job growth slowed to an annualized rate of 1.7 percent. Private service-providing industries accounted for more than 90 percent of the net employment gain, and two sectors—professional and business services and private education and health care—contributed more than 20 percent each. In contrast, manufacturing suffered a net job loss.

From December 2001 through December 2015, job growth slowed to 0.6 percent annually, while real GDP grew at an annualized rate of 1.9 percent. These growth rates were dampened to a large extent by the Great Recession. Private service-providing industries added 14.9 million jobs during the 2001–15 period, while goods-producing industries cut 3.4 million jobs.

Delving into the industry details

From January 1939 through December 2015, employment across sectors has risen and fallen at varied rates. Employment in one sector has shown a net decline over this period, while employment in other sectors has grown much faster than total nonfarm employment. This section examines selected sectors during this period.

Mining and logging

Employment in the mining and logging sector declined by an annualized rate of 0.2 percent, but the industry has experienced strong trend changes. By September 1948, employment had risen to a peak of more than 1 million jobs, then started a longrun decline that lasted through 1972. After this decline, rapid job growth ensued and employment in the sector reached an alltime high of 1.3 million in November 1981 mainly because of gains in oil and gas extraction. Following this record high, job losses returned and employment fell to a record low of 566,000 in April 2003. By 2014, mining and logging employment had recovered to some extent but was still lower than its initial 1939 level. Employment in the sector declined throughout 2015.

Manufacturing

In manufacturing, employment increased by an annualized rate of 0.4 percent. Employment in the sector grew until reaching an alltime peak of 19.6 million in June 1979, then declined and never fully recovered to the peak level. In December 2015, manufacturing jobs totaled 12.3 million and accounted for 8.6 percent of nonfarm employment, compared with 9.1 million and 30.3 percent in January 1939.

Information

Employment in the information sector grew at an annualized rate of 1.2 percent. Through the turn of the century, the sector experienced longrun employment growth that accelerated in the 1990s. In March 2001, employment peaked at 3.7 million, then declined sharply in the years following, with declines led by the publishing and

telecommunications industries. The sector reduced its share of nonfarm employment from 3.7 percent in January 1939 to 1.9 percent in December 2015.

Construction

Construction employment grew at an annualized rate of 2.3 percent over the period, slightly stronger than longrun job growth for total nonfarm industries. Construction employment has been particularly sensitive to business cycles and has experienced large cyclical fluctuations throughout the history of the series, during which it increased its share of nonfarm employment from 3.8 percent to 4.6 percent.

Financial activities

Financial activities also experienced slightly stronger longrun job growth than total nonfarm industries, growing at an annualized rate of 2.4 percent over the period. The sector has experienced less volatility than most other sectors and has increased its share of nonfarm employment from 4.6 percent to 5.7 percent over the period.

Retail trade

Employment in the retail trade sector essentially kept pace with total nonfarm employment, growing at an annualized rate of 2.1 percent over the period. Its share of total nonfarm employment edged up from 10.4 percent to 11.0 percent.

Private education and health services

Private education and health services, the least cyclical sector, has experienced the strongest and most consistent job growth, with 3.7-percent annualized growth over the period. In January 1939, the sector's employment level was 1.4 million, representing 4.6 percent of all nonfarm jobs. By December 2015, employment in the sector had risen to 22.4 million, representing 15.6 percent of all nonfarm jobs. Since 1990, most of the growth in this industry has been concentrated in health care.

Professional and business services

Professional and business services also saw above-average job growth; employment in the sector grew tenfold, from around 1.9 million to 20 million over the period examined. Over the same span, the sector grew at a 3.1-percent annualized rate and increased its share of total nonfarm employment from 6.5 percent to 14.0 percent.

Leisure and hospitality

Employment in leisure and hospitality grew at a strong 2.8-percent annualized rate, increasing its share of nonfarm employment from 6.1 percent to 10.7 percent. Food services and drinking places has been the primary driver of growth within the sector, accounting for 77.4 percent of all jobs added from December 1990 through December 2015.

Other services

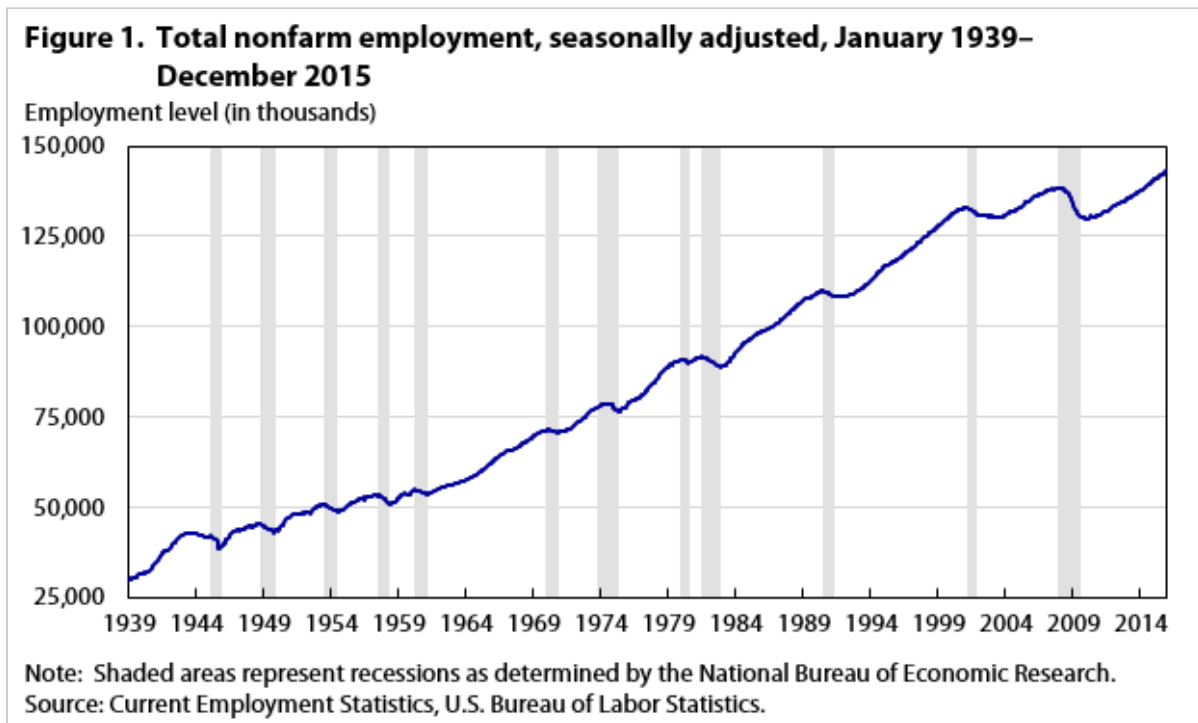
Employment in other services grew at a faster 3.1-percent annualized rate than total nonfarm employment over this longrun period as well, growing from 0.5 million in January 1939 to 5.7 million in December 2015. Its share of total nonfarm employment more than doubled, from 1.8 percent to 4.0 percent, over that period.

Government

Government employment experienced slightly stronger longrun growth than did total nonfarm employment over the period, but government's 2.2-percent annualized employment growth over the period was not uniform. From January 1939 through December 2015, federal government employment rose by an annualized 1.5 percent per year. WWII caused a spike in federal government employment during the early 1940s, with a subsequent decline through 1948. Employment in state and local government combined has risen by an annualized 2.3 percent from December 1955 (the first year of both series) through December 2015. By December 2015, local government accounted for nearly two-thirds of all government jobs.

Many factors affect employment trends—business cycles, changing business practices, and irregular events or shocks. Next, we take a closer look at how some of these trends have affected employment throughout the 1939–2015 longrun period.

Business cycles



CES employment data serve as a major economic indicator of the health of the U.S. economy. The National Bureau of Economic Research (NBER), the organization that determines recession start and end dates, relies on these data for determining business cycle turning points.⁴ Since 1939, employment trends have tended to coincide with business cycles, albeit imperfectly, declining during recessions and rising during recoveries and expansions. (See figure 1). In fact, total nonfarm payroll employment from the CES serves as a primary input for The Conference Board Coincident Economic Index.⁵

Table 3 shows business cycle turning points and corresponding turning points in nonfarm employment since 1939. For most cyclical peaks since 1939, CES employment peaked within a few months of the business cycle peak. The same is not true of the downturns coinciding with the recession of 1945 and the 1973–75 recession. However, the

decline in CES employment led the 1945 recession by 15 months, likely a result of WWII events. In contrast, CES employment lagged behind the 1973 business cycle peak by 8 months.

Table 3. Business cycle and employment turning points, 1939–2015

NBER business cycle dates		Current Employment Statistics employment turning points		Months employment turn leads or lags business cycle turn	
Peak month	Trough month	Peak month	Trough month	Months from NBER peak	Months from NBER trough
February 1945	October 1945	November 1943	September 1945	-15	-1
November 1948	October 1949	September 1948	October 1949	-2	0
July 1953	May 1954	July 1953	August 1954	0	3
August 1957	April 1958	April 1957	June 1958	-4	2
April 1960	February 1961	April 1960	February 1961	0	0
December 1969	November 1970	March 1970	November 1970	3	0
November 1973	March 1975	July 1974	April 1975	8	1
January 1980	July 1980	(1)	(1)	—	—
July 1981	November 1982	July 1981	December 1982	0	1
July 1990	March 1991	June 1990	May 1991	-1	2
March 2001	November 2001	February 2001	August 2003	-1	21
December 2007	June 2009	January 2008	February 2010	1	8

Notes:

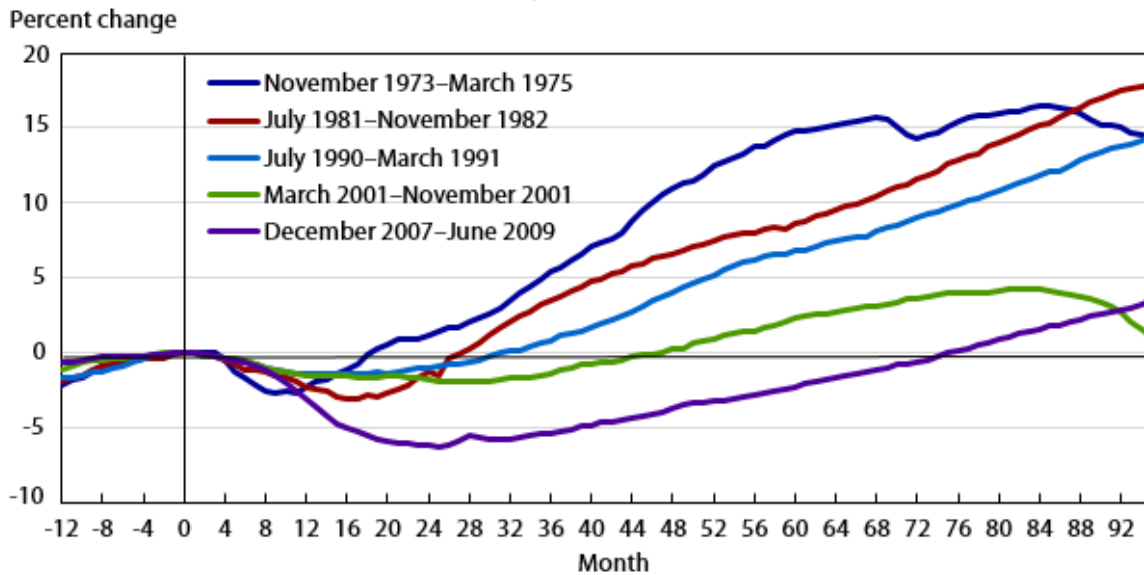
(1) No peak or trough designated because period of downturn did not meet CES criteria for peaks and troughs.

Sources: Current Employment Statistics, U.S. Bureau of Labor Statistics and National Bureau of Economic Research.

Similarly, for all but two of the recessions, the relationship between employment and economic recovery was fairly close. The 2001 recession was the first where employment had not turned up within 3 months of earlier business cycle troughs. Following the 2001 recession, employment continued to fall for nearly 2 years. Jobs losses also continued for 8 months after the 2009 recessionary trough.

The Great Recession

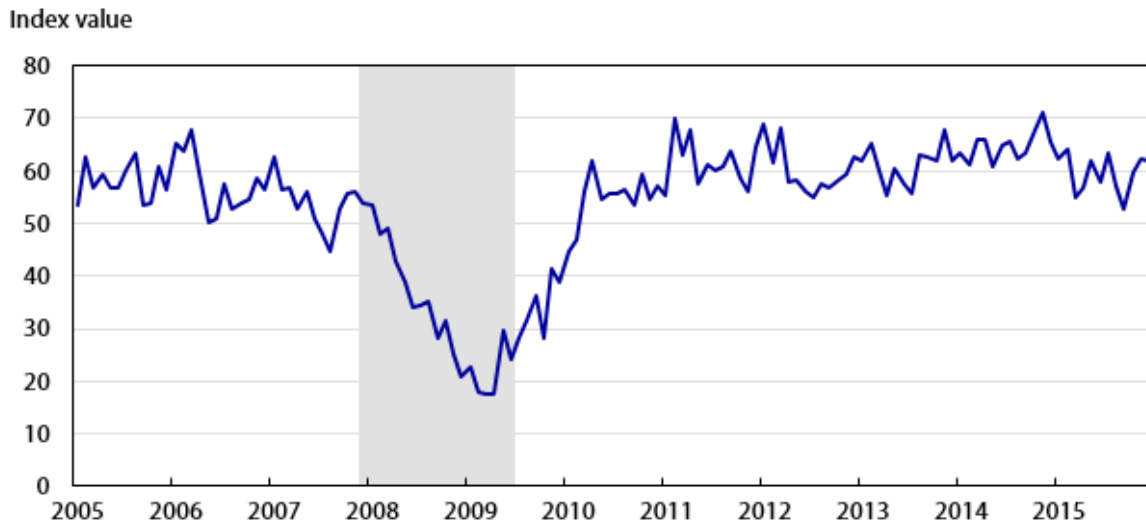
Figure 2. Total nonfarm employment, percent change from employment peak, indexed to respective employment peaks



Source: Current Employment Statistics, U.S. Bureau of Labor Statistics.

The depth and breadth of employment losses during the Great Recession contrast sharply with all other recessions since 1939.⁶ From its peak in January 2008 to its trough in February 2010, nonfarm employment decreased by 8.7 million, a decline of 6.3 percent. Only the job loss during WWII was greater—from November 1943 to September 1945, employment declined by 10.1 percent. Recovery was slow coming out of the Great Recession. (See figure 2.) It took 25 months to lose the jobs, and twice as long (51 months) to recover them by May 2014. This was the longest employment recovery time following any recession since 1939. The next longest recovery, often referred to as the “jobless recovery,” followed the 1990–91 recession, in which employment took 23 months to recover.

Figure 3. Total private 1-month diffusion index, seasonally adjusted, January 2005–December 2015



Note: Shaded area represents the 2007–09 recession as determined by the National Bureau of Economic Research.

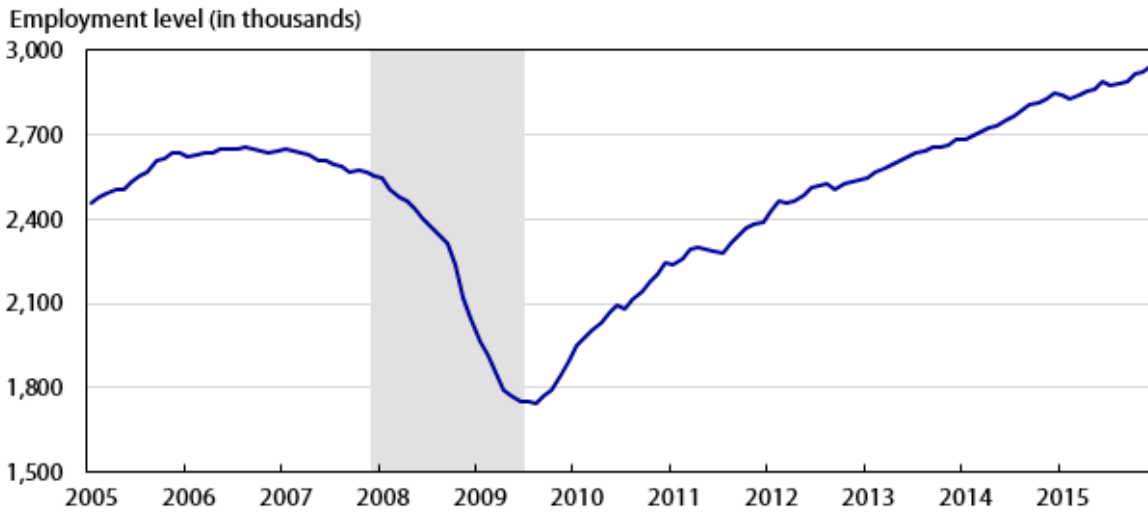
Source: Current Employment Statistics, U.S. Bureau of Labor Statistics.

The breadth of the Great Recession also was widespread among various industries, as illustrated by the 1-month diffusion index for the private-sector industries. The diffusion index fell below 50 in February 2008, and remained below 50 through February 2010. (See figure 3.) In the diffusion index, values less than 50 indicate that more industries are losing jobs than gaining jobs; conversely, values greater than 50 indicate that more industries are gaining jobs than losing them. The index hit a trough of 17.4 in April 2009, 2 months before the recession ended.

Leading and lagging industries

Certain CES data series have been shown to lead business cycle turning points. Employment in the temporary help services industry, for example, is a leading indicator for overall employment cycles. Employment in temporary help services reached a peak in August 2006, 17 months before the peak in total nonfarm employment, and a trough in August 2009, 6 months before the trough in total nonfarm employment. As the economy weakens, businesses across all industries are often willing to shed temporary, contracted workers before their permanent employees. As such, employment in temporary help services will generally decline before total nonfarm employment. During times of recovery, businesses may purchase labor services from temporary help companies while judging the economic climate before they hire permanent employees.⁷ Accordingly, temporary help services employment tends to coincide with upturns in the business cycle, but it still leads changes in overall employment. Figure 4 tracks the employment in temporary help services from 2005 through 2015.

Figure 4. Temporary help services employment, seasonally adjusted, January 2005–December 2015



Note: Shaded area represents the 2007–09 recession as determined by the National Bureau of Economic Research.

Source: Current Employment Statistics, U.S. Bureau of Labor Statistics.

Manufacturing production employees' average weekly hours also serve as a leading indicator for business cycles; this input is included in The Conference Board Leading Economic Index.⁸ Average weekly hours usually decrease before the economy enters a recession because employers typically cut employees' hours before laying them off. Since 1939, the manufacturing workweek has peaked, on average, 10 months prior to the business cycle peak. (See table 4.) While it leads business cycle peaks, the manufacturing workweek is less likely to lead periods of economic recovery. For example, the workweek did not reach a trough until 20 months after the early 2000s recession ended in November 2001.

Table 4. Business cycle and manufacturing workweek turning points, 1945–2015

NBER business cycle dates		Manufacturing workweek turning points		Months manufacturing workweek turn leads/lags business cycle turn	
Peak month	Trough month	Workweek peak	Workweek trough	Number of months from NBER peak	Number of months from NBER trough
February 1945	October 1945	November 1943	May 1946	-15	7
November 1948	October 1949	December 1947	April 1949	-13	6
July 1953	May 1954	March 1953	January 1954	-4	-4
August 1957	April 1958	November 1955	February 1958	-21	-2
April 1960	February 1961	May 1959	December 1960	-11	-2
December 1969	November 1970	October 1968	December 1970	-14	1
November 1973	March 1975	March 1973	March 1975	-8	0
January 1980	July 1980	March 1979	July 1980	-10	0

See footnotes at end of table.

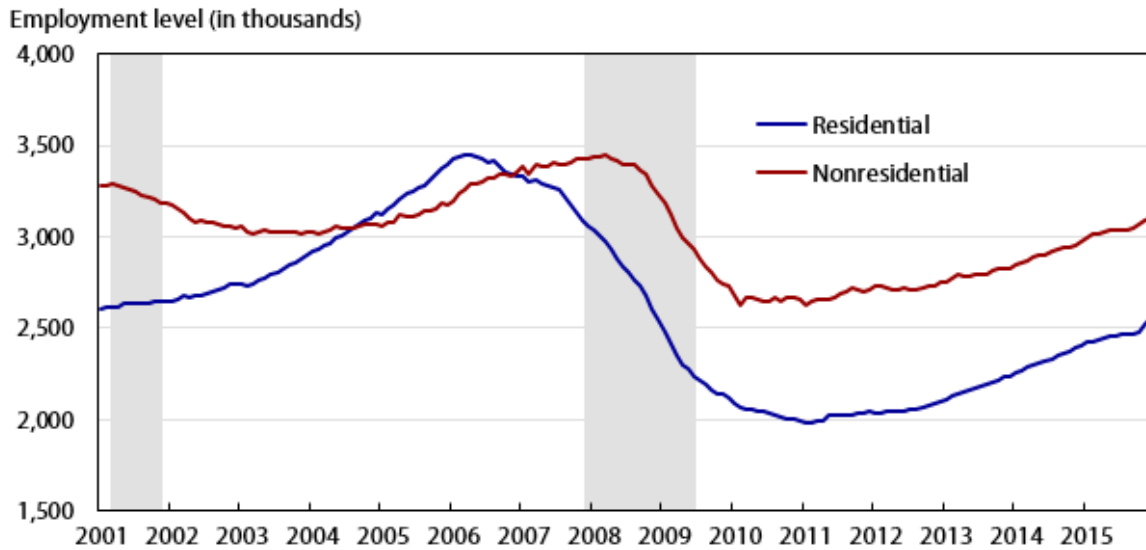
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Peak month	Trough month	Workweek peak	Workweek trough	Number of months from NBER peak	Number of months from NBER trough
July 1981	November 1982	May 1981	January 1982	-2	-10
July 1990	March 1991	February 1989	March 1991	-17	0
March 2001	November 2001	April 2000	July 2003	-11	20
December 2007	June 2009	March 2008	May 2009	3	-1

Sources: Current Employment Statistics, U.S. Bureau of Labor Statistics and National Bureau of Economic Research.

For most industries, employment trends track business cycles; however, weakness in certain economic sectors may sometimes signal turning points. Construction serves as an interesting example: during the past 12 business cycle peaks, employment in the construction sector experienced a coincident peak in 4 instances, peaked 5 or more months prior in 6 instances, and failed to reach a proximate employment peak in the 2 remaining instances. Construction employment peaked in April 2006, 20 months before the start of the Great Recession. This change in employment trend generally tracked the U.S. housing bubble, a period during which new single-family home prices rose rapidly until peaking in 2007, then declined sharply the next several years before reaching a trough in 2011.⁹ Prices have since rebounded sharply, surpassing the 2007 peak by 8.0 percent as of 2015. Residential construction exhibited an earlier lead time into the housing bust and ensuing recession than nonresidential construction; employment in residential building and residential specialty trades peaked in early 2006, while nonresidential construction employment peaked in early 2008.¹⁰ (See figure 5.)

Figure 5. Construction employment, residential and nonresidential, seasonally adjusted, January 2001–December 2015



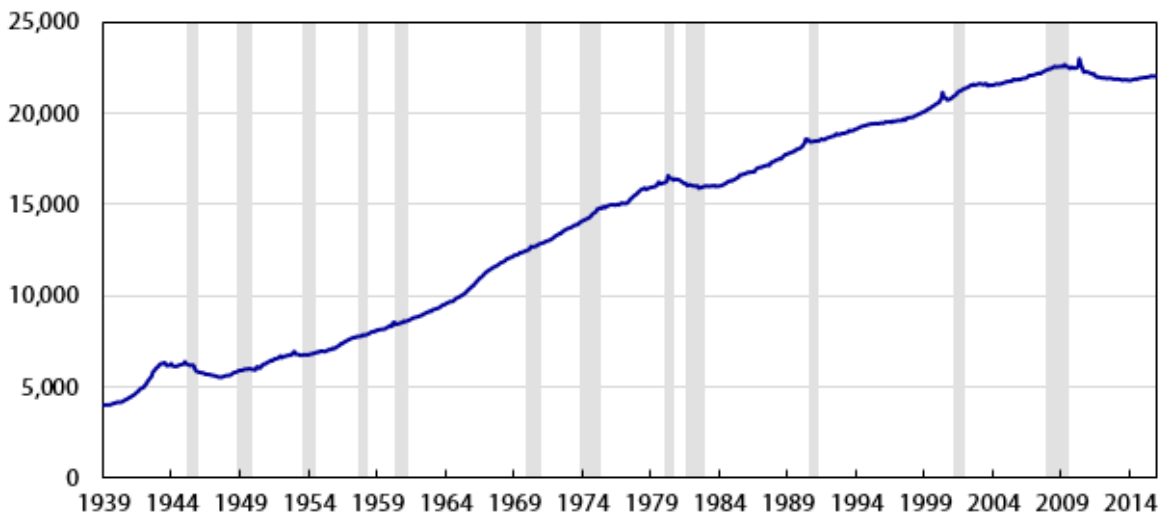
Note: Shaded areas represent recessions as determined by the National Bureau of Economic Research.
Source: Current Employment Statistics, U.S. Bureau of Labor Statistics.

Economic shocks in one industry can transfer to related industries. As the housing bubble started to have an impact on the construction industry, weakness quickly moved to financial activities; complementary industries such as mortgage finance and real estate were particularly affected. Financial activities reached an employment peak in December 2006, 13 months before total nonfarm employment peaked. Shortly thereafter, housing prices began to decline and both mortgage delinquency rates and home foreclosures increased sharply, particularly among homeowners with subprime home loans. The financial activities industry lost 718,000 jobs from December 2006 to February 2011.

The cyclical trends for government employment tend to lag business cycle changes. Government entities at the federal, state, and local levels set budgets based on estimates of future tax revenues and other income streams. As a result, expenditures, including those for hiring, are based on older economic data. When the economy weakens, tax revenues may fall short of expectations. This, in turn, could cause government entities to adjust their workforce through hiring freezes or layoffs.

Figure 6. Government employment, seasonally adjusted, January 1939–December 2015

Employment level (in thousands)



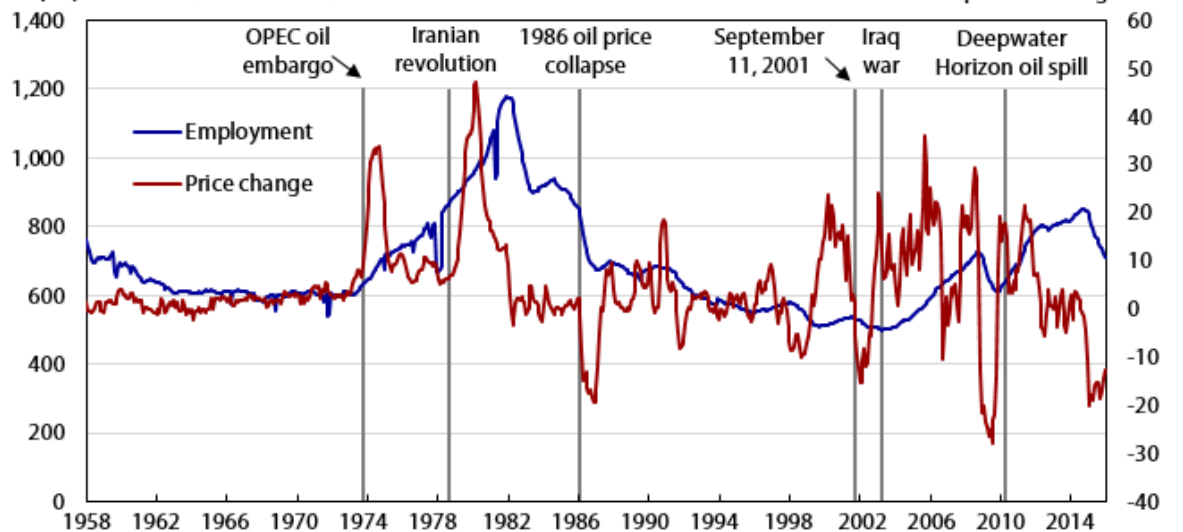
Note: Shaded areas represent recessions as determined by the National Bureau of Economic Research.
Source: Current Employment Statistics, U.S. Bureau of Labor Statistics.

Post-WWII government employment has grown more slowly or turned down following business cycle turning points.¹¹ During the 1980 recession (January 1980–July 1980), government employment did not peak until April 1980, 3 months after the business cycle peak. Following the start of the Great Recession, employment in government did not peak until April 2009, 16 months after the business cycle peak (See Figure 6).

Acyclical employment

Figure 7. Mining employment and over-the-year energy price percent change, seasonally adjusted, January 1958–December 2015

Employment level (in thousands)



Source: Current Employment Statistics and Consumer Price Index, U.S. Bureau of Labor Statistics.

Employment in most industries moves with business cycles. But for two industries in particular, mining and health care, factors other than the prevailing business cycle tend to determine employment patterns. Employment in mining tends to respond to changing energy prices. Health care employment has continued on an upward trend, regardless of business cycles. The mining industry is particularly reactive to rising and falling energy prices. Since 1958, events ranging from oil embargos, unrest in oil producing countries, and terrorist attacks to natural disasters have coincided with jumps in energy prices. (See figure 7.) In 1974, a sharp spike in crude oil prices coincided with the oil embargo of 1973, which cut oil production and banned petroleum exports to the United States.¹² Mining firms responded with a rapid buildup of domestic production and employment. As energy prices spiked again in 1980 following the Iranian Revolution and strikes at Iranian oil refineries, mining employment continued to rise. When energy prices fell in the wake of the 1986 oil price collapse, and again after the early 2000s recession (March 2001–November 2001), mining employment declined. Subsequent events, including the September 11th terrorist attacks, the Iraq War, hurricanes, and a major oil spill in the Gulf of Mexico, caused energy prices to increase dramatically. With these price gains, mining employment grew rapidly, then declined sharply when prices fell.

As energy prices were rising throughout much of the last decade, domestic oil and gas producers began taking advantage of improved methods for extracting oil. The expansion of one method in particular, hydraulic fracturing (or “fracking”), allowed the United States to become “the world’s largest producer of crude oil and related field production for the first time in decades.”¹³ The resulting increase in oil supply, combined with a deceleration in economic growth in China and elsewhere in the world, has led to a sharp decline in oil prices since late 2014.

Health care employment is often described as “recession proof” because it generally does not decline during economic downturns. Health care employment has grown consistently since 1958; there have been only 8 instances of over-the-month job losses, and 2 of those instances occurred as a result of strikes.¹⁴ Previous studies have described the rate of growth in hospital employment as countercyclical: when general business conditions are weak, hospital employment tends to grow.¹⁵ During the Great Recession, health care added 431,000 jobs, even as the economy lost 7.4 million jobs. Of the jobs added during that period, nearly a quarter (102,000) were in hospitals.

Some industries have demonstrated sharp spikes or drops in employment that quickly returned to normal. The federal government, for example, experiences a spike in employment every 10 years for the collection of the decennial census. For the 2010 Census, more than half a million temporary workers were hired to count the population; most were hired in May 2010, then laid off over the next several months.¹⁶

Globalization

Employment trends in the manufacturing sector reflect some of the earliest movements in the United States toward globalization, whereby U.S. firms incorporate more foreign-made goods into their final output or, in the most extreme cases, move all production to foreign soil. Manufacturing employment in the U.S. reached an alltime peak in June 1979. Since then, the long-term employment trend has been downward. According to the Bureau of Economic Analysis, manufacturing accounted for 12 percent of value-added GDP in 2014, down from 26 percent in 1947.¹⁷

The losses were particularly stark in apparel, which, since January 1990, has lost 86 percent of its employment. Additionally, in the second quarter of 2015, the United States imported 12 times the value of apparel goods that it exported.

Although the CES survey cannot be used to determine if jobs moved offshore or if job losses resulted from foreign competition, export and import data help explain why the manufacturing industry has shrunk since 1979. The United States currently imports more manufactured goods than it exports. On the basis of trade data from the Census Bureau, the United States experienced a positive balance of payments in net exports of goods prior to 1970, indicating more goods were exported than imported. During the 1970s the balance shifted, and in every year since 1976 the country has experienced a negative balance of payments in goods.¹⁸

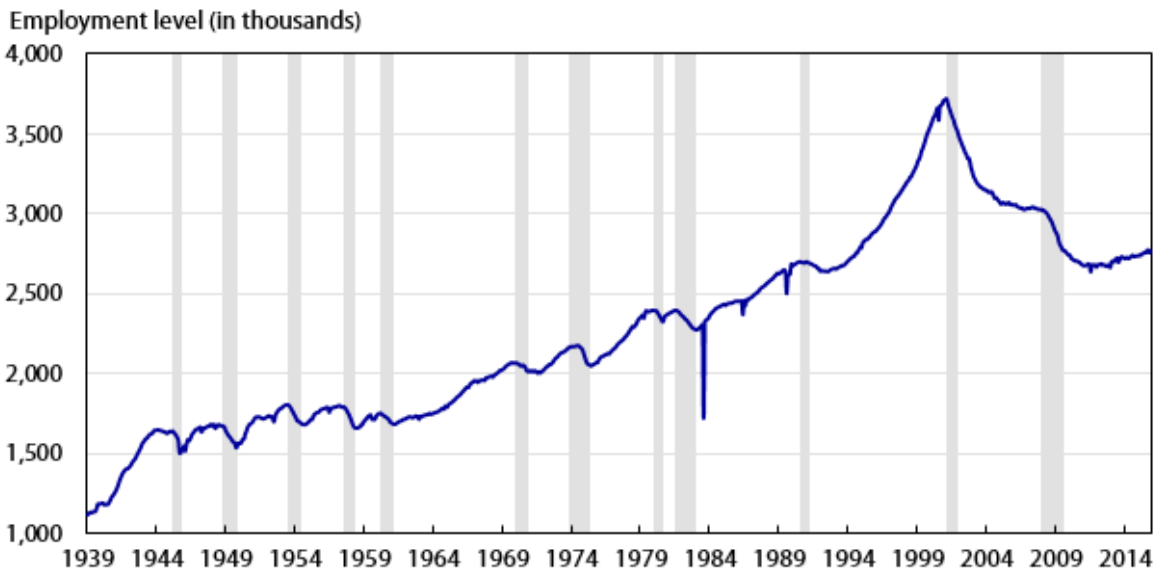
Contrasting with U.S. trade in goods, service-providing industries have seen an employment uptick that started in the 1970s. Since 1971, the United States has run a surplus in its balance of payments for services each year. But because of the trade imbalance present for goods-producing industries, the overall balance of payments has shown a deficit each year since 1976.

New and emerging industries

In addition to reacting to cyclical changes, employment trends have been affected by changing business practices. In fact, when the NAICS was initially developed in the 1990s, special attention was given to capturing such changes—the inclusion of production-oriented classifications for new and emerging industries, expanded industry detail for service providers, and efforts to identify industries that produce advanced technologies.¹⁹ One sector met each of these NAICS criteria—the information sector.

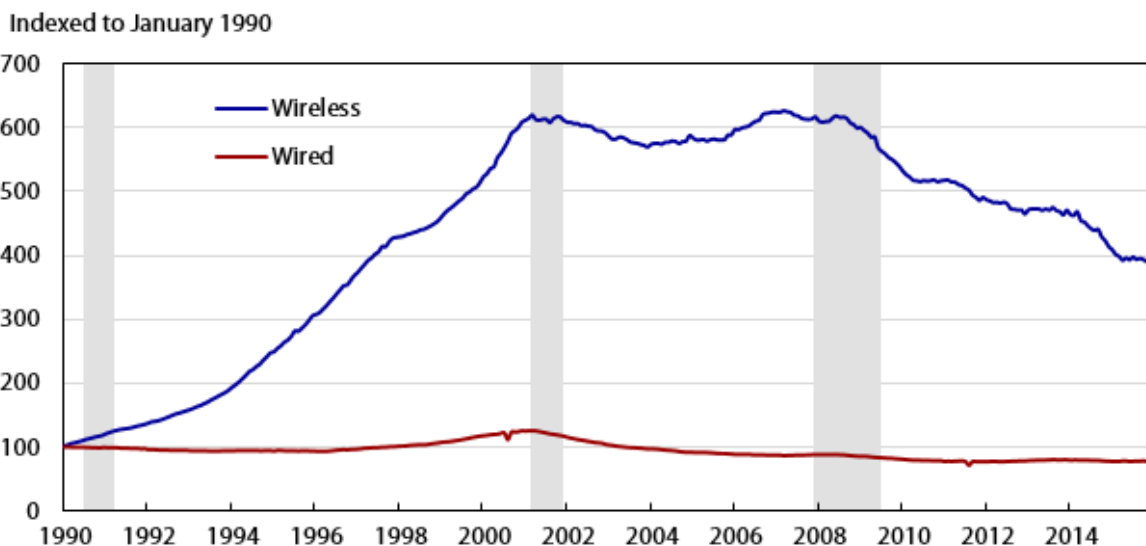
The information sector, which includes publishers, motion picture producers, broadcasters, and telecommunication services, captures new and emerging industries, such as Internet hosting and wireless telecommunication. The sector has experienced significant structural changes with the introduction of advanced technologies, including satellites, cell phones, the Internet, and other wireless communications. The sector enjoyed steady employment growth through the 1980s; this growth accelerated during the 1990s, then entered a long-term decline after employment peaked in March 2001. (See figure 8.) This decline coincided with the collapse of the dot-com bubble.

Figure 8. Information employment, seasonally adjusted, January 1939–December 2015



Telecommunications is a component of the information sector that has evolved rapidly because of structural changes. Since 1990, employment in wired telecommunication has declined precipitously, while its wireless counterpart has gained jobs. This difference is largely explained by constantly improving technology and the increased popularity of cell phones and other wireless devices.

Figure 9. Telecommunications employment, seasonally adjusted, January 1990–December 2015



Employment in wired telecommunications carriers peaked in December 2000 and has drifted down since then. By December 2015, the industry had lost about 371,000 jobs, or 38.7 percent of its total employment. In contrast, employment in wireless telecommunications rose rapidly during the 1990s and remained relatively flat until early in

the Great Recession, but has trended down since March 2007, with 79,000 jobs lost through December 2015. (See figure 9.) Despite these different trends, employment in wired telecommunications (589,000) was still substantially higher than in wireless telecommunications (127,000) in December 2015. Two factors help explain the higher employment in wired telecommunications: (1) many workplaces still prefer wired networks because they are more secure than their wireless counterparts, and (2) the maintenance and repair for these networks is far more labor intensive than required for wireless networks.²⁰

An area that has been greatly affected by changing technology is publishing. Publishing industries have reduced employment by about 31 percent since January 2001, coinciding with a strong movement towards online, digital content and away from paper books, magazine, and newspapers. Newspapers, for instance, have significantly cut back on daily print editions.²¹ In 2014, sales of e-books grew to \$3.37 billion, representing a share similar to that of hardback books.²²

Changing business paradigms

Like information, the retail sector has been greatly affected by the growth of the Internet. The transition of consumers to online shopping has affected employment in retail trade as well. Since the early 2000s, online retail sales have increased steadily and, as of the fourth quarter of 2015, made up 7.5 percent of total retail sales.²³

Despite its small share of retail employment, recent employment trends in electronic shopping and electronic auctions illustrate the transition in consumer behavior from shopping in brick-and-mortar stores to shopping online. During the 1990s, job growth in electronic shopping and electronic auctions accelerated and, after falling during the 2001 recession, reaccelerated sharply. From December 1990 to December 2015, the industry's employment grew by more than 420 percent, while job growth was much slower in all other retail industries. (See table 5.)

Table 5. Employment and employment change, retail trade and component industries, seasonally adjusted (in thousands), 1990–2015

Industry	Employment		Employment change	
	December 1990	December 2015	Level	Percent
Retail	13,088.1	15,760.8	2,672.7	20.4
Motor vehicle and parts dealers	1,468.5	1,973.9	505.4	34.4
Furniture and home furnishings stores	420.9	467.4	46.5	11.0
Electronics and appliance stores	448.7	524.5	75.8	16.9
Building material and garden supply stores	877.0	1,258.4	381.4	43.5
Food and beverage stores	2,791.1	3,067.5	276.4	9.9
Health and personal care stores	791.9	1,033.2	241.3	30.5
Gasoline stations	904.7	915.4	10.7	1.2
Clothing and clothing accessories stores	1,291.6	1,359.1	67.5	5.2
Sporting goods, hobby, book, and music stores	465.8	628.4	162.6	34.9
Music and book stores ⁽¹⁾	139.2	119.2	-20.0	-14.4
General merchandise stores	2,478.9	3,164.4	685.5	27.7
Miscellaneous store retailers	736.9	844.3	107.4	14.6
Nonstore retailers	412.1	524.3	112.2	27.2

See footnotes at end of table.

Table 5. Employment and employment change, retail trade and component industries, seasonally adjusted (in thousands), 1990–2015

Industry	Employment		Employment change	
	December 1990	December 2015	Level	Percent
Electronic shopping and mail order houses	156.3	351.8	195.5	125.1
Electronic shopping and electronic auctions	41.3	215.3	174.0	421.3

Notes:

(1) This is a combination of musical instruments and supplies stores, book stores, and news dealers.

Source: Current Employment Statistics, U.S. Bureau of Labor Statistics.

Online shopping also has had a major impact on traditional brick-and-mortar retail stores. Employment in music and book stores has declined by nearly 15 percent since 1990. With the increased popularity of digital music, employment in traditional music stores declined substantially. Another consequence of the prevalence of online shopping is that consumers are able to search out the best deals, weakening profit margins; this, in turn, negatively affects employment in traditional retail stores.²⁴

Contrasting with the negative employment impacts on brick-and-mortar stores, online shopping has positively impacted employment for couriers and messengers. From January 1990 to December 2015, the industry grew by 255,000 jobs, or 68.9 percent. The industry tempered its employment growth trend, however, by improving productivity through technology. For example, UPS enhanced its shipping technology by improving sorting and tracking capabilities and, thus, labor productivity. These improvements likely helped the company expand its annual delivery volume to 4.7 billion packages and documents in 2015.²⁵

Economic shocks

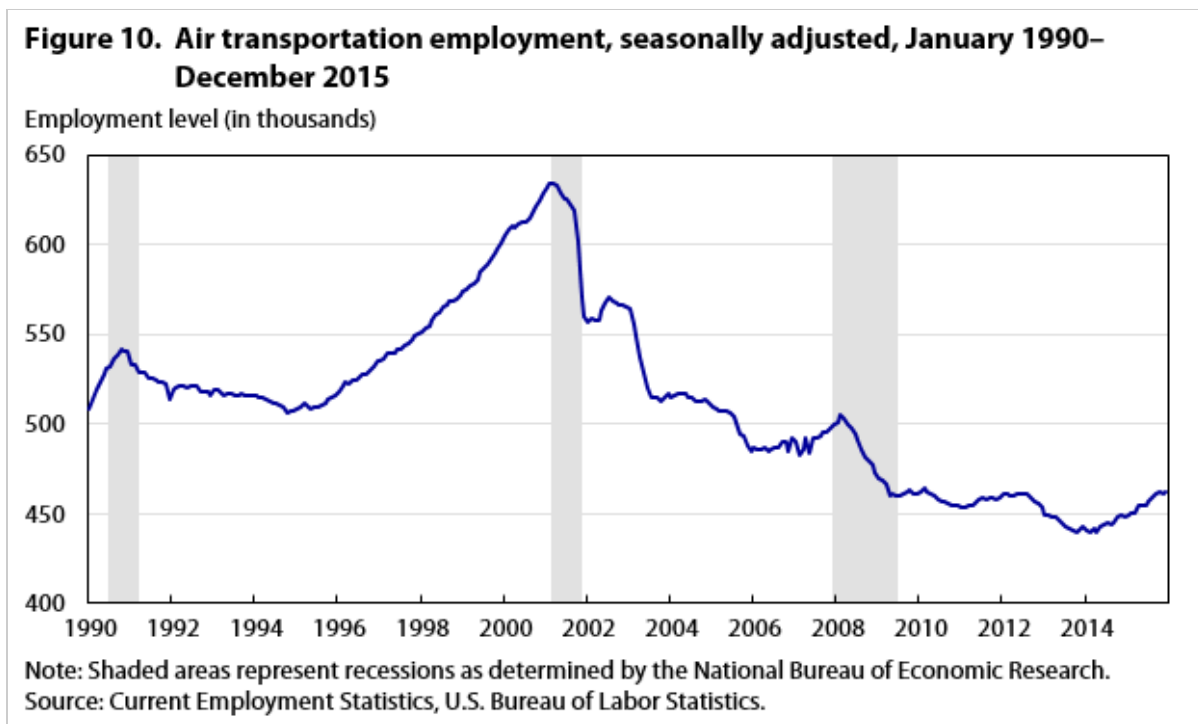
While longrun employment trends are often the result of changes to the overall economy and business practices, outsized, short-term fluctuations may occur in response to unusual large-scale events or shocks.

WWII caused immense employment changes in several industries. Although the CES program excludes military employment, changes in civilian jobs within the Department of Defense and other industries can still be observed. During WWII, civilian employment in the Department of Defense jumped by 868,000 from December 1941 to November 1944. In the years following the war, employment fell to prewar levels, only to spike again in the early 1950s during the Korean War.

During WWII, ship and boat building employment spiked as the military built up its fleet of warships and cargo vessels. Ship and boat building added 1.3 million jobs from January 1940 to December 1943 but shed all of the jobs gained by October 1949. Similarly, the construction sector saw an increase in employment. From January 1940 to an employment peak in July 1942, construction added 1.4 million jobs, an increase of 122 percent. The sector subsequently shed those gains by June 1944. Employment in these industries has not experienced the same sort of shocks in more recent wars.

Severe weather events can have an impact on employment and hours. The reference period for the CES survey is the pay period that includes the 12th of the month; workers receiving pay for any part of the pay period are considered employed. For severe weather to affect national employment, it must meet the following criteria: transpire around the 12th of the month, have an extended duration, and occur in either densely populated or geographically large areas. When severe weather occurs, average weekly hours often drop in industries where work is concentrated outdoors, such as construction or leisure industries. When conditions affect transportation infrastructure, they can also affect total nonfarm employment. For example, the blizzard of January 1996 coincided with a drop of 19,000 in nonfarm employment, compared with an average gain of 180,000 per month over the prior 12-month period. Employment then rebounded the following month with an increase of 432,000.

Sudden changes in demand for specific goods or services can also affect employment. For example, after the September 11th attacks, travelers became more reluctant to fly, which caused a significant reduction in demand for air travel.²⁶ Employment in air transportation dropped sharply in the 3 months following September 2001; job losses totaled 59,000, a 9.6-percent decline. Prior to the attacks, the industry had experienced steady job growth that started in the mid-1990s. After the attacks, employment in air transportation continued to fall and, despite an upward trend in 2015, remains about 25 percent below its September 2001 level. (See figure 10.)



Strikes typically have a negative impact on employment. The CES survey measures the number of people on payrolls—that is, those actually getting paid for work or for leave that occurred during the reference pay period. Thus, people on strike for the entire period are not counted as employed, because they are not on the payroll. When workers strike, employment falls in the strikers' industry. After the strike is resolved and employees return to work, employment rebounds. For example, 640,000 workers went on strike against AT&T from August 7, 1983 to August 28, 1983.²⁷ During the strike, employment in the communications industry fell by 648,000 in August; it rebounded by the same amount in September. Table 6 shows strikes that affected employment by 100,000 or more.²⁸

Table 6. Strikes affecting Current Employment Statistics (CES) employment data by more than 100,000, 1975–2015

Date	Industry (Standard Industrial Classification)	Effect on CES employment
December 1977	Coal mining (12)	160,000
January 1978	Coal mining (12)	160,000
July 1980	General building contractors: residential buildings (15)	105,000
April 1981	Coal mining (12)	160,000
May 1981	Coal mining (12)	162,000
August 1983	Telephone communications—AT&T (481)	640,000
August 1989	Telephone communications (481); electrical apparatus and equipment, wiring supplies, and construction materials (5063); computer processing and data preparation and processing services (7374)	125,000
August 1997	Trucking and courier services, except air—United Parcel Service (421)	185,000

Notes: These strikes are based on Standard Industrial Classification system (SIC) data. When CES converted from SIC to the North American Industry Classification System, telecommunications was reconstructed back to 1990.

Source: Current Employment Statistics, U.S. Bureau of Labor Statistics.

Employment as it relates to the economy

BLS publishes its monthly Employment Situation news release typically on the first Friday following the reference month. The news release contains detailed national employment, hours, and earnings data from the CES survey, along with the unemployment rate and labor force statistics from the Current Population Survey. Data from the CES survey serve as indicators of current economic trends in the United States and, therefore, rank high among the most widely watched economic statistical series in the country and around the globe.

Conclusion

Over the 100 years since CES began collecting data from a handful of manufacturing industries, the U.S. economy has experienced substantial transformations. Some of these transformations have caused significant trend changes for certain sectors of the economy. From January 1939 to December 2015, one sector lost jobs, others experienced substantial growth, and still others simply kept pace with total nonfarm employment growth over the period.

SUGGESTED CITATION

Lyda Ghanbari and Michael D. McCall, "Current Employment Statistics survey: 100 years of employment, hours, and earnings," *Monthly Labor Review*, U.S. Bureau of Labor Statistics, August 2016, <https://doi.org/10.21916/mlr.2016.38>.

NOTES

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- [3](#) Labor productivity annual data is only available back to 1948. See www.bls.gov/lpc/ for more information.
- [4](#) For a comprehensive list of the U.S. business cycle expansions and contractions, see <http://www.nber.org/cycles.html>.
- [5](#) For a comprehensive list of inputs for the Conference Board Coincident Economic Index, see https://www.conference-board.org/pdf_free/press/US%20LEI%20-%20Tech%20Notes%2082015.pdf.
- [6](#) Monthly employment data are not available for the period of the Great Depression, which persisted for 43 months from August 1929 to March 1933.
- [7](#) Temporary help service establishments provide workers to all industries, but the CES survey does not track where employees are ultimately placed. As a result, CES data do not show how employment in individual industries is affected by labor contracted from temporary help firms.
- [8](#) For a comprehensive list of inputs for The Conference Board Leading Economic Index, see <https://www.conference-board.org/data/bcicountry.cfm?cid=1>.
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Awareness and usage of the sharing economy

Jacob Galley

The sharing economy (also known as collaborative consumption, the on-demand economy, the peer economy, or the access economy), formed from the business model predicated on peer-to-peer transactions and popularized by such companies as Uber, Airbnb, and TaskRabbit, has grown exponentially in recent years. These services are widely touted as a means of reducing costs and improving access to a wide variety of goods and services. But for Americans, awareness and usage of these services vary greatly across demographic and geographic backgrounds. In the paper, [“Shared, collaborative, and on demand: the new digital economy”](#) (Pew Research Center, May 19, 2016), Aaron Smith provides a summary of data on participation in the sharing economy from a sample of about 4,800 respondents. The results reveal the existing gap in the awareness and use of these platforms among geographic and demographic groups of Americans.

The study focused on 11 broad categories of services available in the sharing economy—including ride-hailing apps, home-sharing services, online fundraising (also known as “crowdfunding”), and online retailers for secondhand goods. It found that 72 percent of Americans had used at least 1 of the 11 types of services identified. However, 28 percent had not used any of the online services, and many more were unfamiliar with the vocabulary used to describe these services. Sixty-one percent had not heard the term “crowdfunding,” 73 percent had not heard of the “sharing economy,” and 89 percent were unfamiliar with the term “gig economy.”

The study found that the use of shared services varied greatly on the basis of income, education, and other demographic characteristics. For example, members of households with relatively high incomes (\$100,000 or more a year) were 3 times more likely than those of households with relatively low incomes (less than \$30,000 a year) to have used four or more of these services. College graduates were also more likely to use these services. Thirty-nine percent of college graduates have used at least one of these services, compared with 8 percent of those with a high school diploma or less. Younger adults were also more likely to have used the shared and on-demand services. About one-third of Americans ages 18–44 have used 4 or more of these types of services, while 44 percent of those age 50 and over have never used any of the services. The disparities are also geographic in nature, with urban residents being about twice as likely as rural residents to have used at least four of the 11 services.

The study went on to examine Americans’ opinions of contentious issues surrounding these services. When it comes to the employment relationship between ride-hailing services and their drivers, 66 percent of respondents described the drivers as independent contractors, working for themselves, who use the service to connect with customers. Twenty-three percent said they are employees who should be viewed as working for the service. However, about two-thirds of ride-hailing service users agree that both the driver and the app service are responsible for ensuring drivers are trained and that the vehicles are clean and safe. With regard to the debate about the regulation of such services, 42 percent think that these services should *not* be required to follow the

same rules and regulations as traditional taxi companies, while 35 percent believe that they should follow the same rules.

The research provides valuable insight into the evolving economy and the views Americans have toward the relatively new phenomenon of shared, collaborative, and on-demand services.

One hundred years of Current Employment Statistics—an overview of survey advancements

To help mark the Monthly Labor Review's centennial, the editors invited several producers and users of BLS data to take a look back at the last 100 years. In 1915, the United States was just beginning to develop as a global economic power. Feeling the need to accurately measure employment in this emerging economy, BLS published a modest set of data on employment in four manufacturing industries. Eventually, this initial effort would evolve into the Current Employment Statistics (CES) program. This article summarizes changes in the CES program over the past century, during which the size, stature, and scope of the survey have grown alongside those of the country whose economy it measures.



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Employment estimates from the U.S. Bureau of Labor Statistics (BLS) Current Employment Statistics (CES) survey are among the world's most watched economic data.¹ Monthly data released by CES are used by federal and state government policymakers, central bankers, the business community, and trade unions. It is exciting to consider, then, that this prominent program originated 100 years ago, starting with the publication of data for just four manufacturing industries.

At the beginning of the 20th century, the primary source of data on employment by industry came from a census of manufactures, which was conducted every 5 years by the U.S. Census Bureau. By 1915, many states were compiling manufacturing employment statistics, but only Massachusetts, New York, and New Jersey had reasonably complete data, and, because of industrial specialization in these states, these data failed to accurately represent manufacturing employment on a national basis.

Figure 1. First CES release of monthly employment and earnings data

NUMBER OF EMPLOYEES AND AMOUNT OF EARNINGS IN IDENTICAL ESTABLISHMENTS IN CERTAIN INDUSTRIES DURING ONE WEEK OF OCTOBER AND NOVEMBER, 1915.

Industry.	Establishments reporting.	Employees.			Earnings.		
		Number on pay roll in—		Per cent of increase (+) or decrease (—).	Amount of pay roll in—		Per cent of increase (+) or decrease (—).
		October.	November.		October.	November.	
Boots and shoes.....	66	54,517	57,551	+5.6	\$688,724	\$752,578	+9.3
Cotton goods.....	56	44,665	44,518	— .3	338,079	349,371	+3.3
Cotton finishing.....	14	12,422	12,548	+ .1	136,349	138,207	+1.4
Hosiery and underwear...	57	30,494	30,836	+1.1	274,851	278,690	+1.4
Iron and steel.....	65		104,782			1,664,180	

Source: U.S. Bureau of Labor Statistics.

The first issue of the BLS *Monthly Review* (later to become the *Monthly Labor Review*), published in July 1915, featured employment statistics for a variety of countries. Upon publication, it was apparent that data for the United States were far less complete than those for countries such as Great Britain, Germany, and France. To address this deficiency, 3 months later, BLS began to publish monthly data on employment and total payrolls for the boots and shoes, cotton goods, cotton finishing, and hosiery and underwear industries, marking the beginning of the modern-day CES survey. (See figure 1.) Today, the CES program surveys approximately 623,000 worksites and publishes well over 10,000 data series. This article outlines *some* of the key advancements of the CES program over the past century.²

Data publication

Since the inception of CES, federal government commissions, statistical associations, and economic circumstances helped the program expand its industry coverage and types of data published. In 1916, CES published data for nine additional manufacturing industries, and the sample size grew to 574 establishments, covering employment of 519,000. Then, in response to a committee on employment statistics appointed by President Warren G. Harding, the program was again expanded in 1923, to 52 manufacturing industries. Six years later, in 1929, the American Statistical Association recommended a further expansion of industry employment coverage, and publication began for 11 nonmanufacturing industries. To accommodate this expansion, CES increased the sample size to 34,000 establishments. The collection of production-employee hours started in 1932, and CES began to publish data on average weekly hours and average hourly earnings, as opposed to the total gross payroll hours that had been published initially.

By 1935, CES was publishing series on employment and total payroll, hours, and earnings of production employees at the national level for total manufacturing, and the coverage expanded to 90 detailed manufacturing

industries and 21 nonmanufacturing industries. In 1936, CES published its first national estimate of total nonfarm wage and salary employment.

Responding to the economic demands brought on by World War II, CES introduced data series for 67 additional manufacturing industries. These were industries that were deemed important to supporting the war effort. Also notable was the introduction of semiannual data on the employment of women in manufacturing, although this series was soon discontinued because of postwar federal budget reductions.

In 1947, the 1945 Standard Industrial Classification (SIC) system was implemented for manufacturing industries, replacing a classification based largely on systems used by the Censuses of Manufactures and the Censuses of Businesses taken in the 1920s and 1930s. Nonmanufacturing industries were classified in accordance with the 1942 Social Security Board Classification. In 1958, the SIC system was adopted for all industry series published by BLS. That system, with periodic updates, remained the basis for CES classification until it was replaced with the North American Industry Classification System (NAICS)³ in 2003. The expansion of the sample to include all nonfarm nonmanufacturing industries began in 1964, allowing for the first publication of average hourly earnings at the total private level in 1967. In 1971, an hourly earnings index for production workers was published. CES diffusion indexes, which measure the dispersion of employment change across industries (rather than the magnitude of that change), were introduced in 1974. In 1988, new diffusion indexes, with a broader industry base, and an additional index for manufacturing were published.

In response to recommendations from the National Commission on Employment and Unemployment (also known as the Levitan Commission) in 1979, the CES program published real average hourly earnings—earnings adjusted to account for price changes—for the first time in 1982. That same year, addressing the Levitan Commission’s finding that CES industry detail was inadequate for the large and growing service-producing sector, CES expanded its sample size and began the publication of data for 82 additional service-sector industries.

In 2003, the CES survey underwent a major redesign. In addition to introducing substantial sample and methodological changes—discussed elsewhere in this article—CES shifted from an SIC-based to a NAICS-based industry classification. Because of this conversion, time-series histories were reconstructed at that time.

In 2004, CES began planning for the collection and production of hours and earnings data for all employees—data that had previously been produced only for production and related employees. Because collection of these data would increase the burden on survey respondents, in 2006 CES discontinued the collection and publication of employment estimates for women employees. CES further planned to eliminate the collection and publication of employment, hours, and earnings data for production and nonsupervisory employees. After receiving more than 5,000 letters of complaint concerning the elimination of women-employee data, CES reinstated this series in 2007 and shelved plans to eliminate production-employee data. In 2008, CES began to publish experimental all-employee hours and earnings series for the nation and, in 2011, the program began to publish official all-employee hours and earnings for the nation, states, and metropolitan statistical areas. So, a survey started a century ago with the publication of employment data for 4 manufacturing industries has grown to cover more than 900 industries. And the data scope of the survey—in 1915, only employment and gross payroll data were published—has grown as well. At the national level, the CES program currently produces over 2,200 employment series, over 2,600 hours and earnings series, and about 8,700 special derivative series,⁴ such as average weekly earnings, various indexes, and constant-dollar earnings. And at the state and metropolitan statistical area levels, CES

produces over 19,000 employment series, over 2,700 hours and earnings series, and about 1,300 derivative average weekly earnings series.

Sample design

Today, the CES sample is a simple, stratified random sample of worksites—a design that reflects contemporary standards for sample-based surveys. One hundred years ago, however, probability sampling⁵ had not emerged as the standard for such surveys, and, during the first few decades of its existence, the CES survey had no formal sample design.

The early survey predominantly measured employment in selected manufacturing industries, which were dominated by large firms. Therefore, even in the absence of a uniform survey design, sampling the large firms resulted in adequate coverage of the universe. As the survey expanded into the service-providing industries, which were dominated by smaller firms, this approach was no longer sufficient.

In the 1940s, research focusing on this deficiency determined that substantial improvement could be realized by stratifying the sample into two size classes and using a ratio estimator. This was a movement toward probability sampling, without actually introducing a probability sample. The approach was validated by research conducted in 1963,⁶ but this research also suggested that the most practical course—given the cost, risk, and difficulty of soliciting an entirely new sample—was to implement a quota design⁷ using the current sample. Quota samples are so called because sample units are selected on the basis of a quota, or predetermined characteristics. These characteristics are assumed to occur in the same proportion in the sample as they do in the entire population. The accuracy of a quota sample depends on those administering the sample and their knowledge of the distribution of relevant characteristics in the population. For CES estimates, the sample was stratified by state, detailed industry, and establishment size. This sample design was first implemented in 1964, although CES recognized that the sample was skewed toward larger firms and that, as a nonrandom sample, it might not represent the universe. The quota sample was used by BLS throughout the 1970s and 1980s, with only minor modifications.

Randomly drawn samples help reduce bias resulting from some members of the population being less likely to be included in the sample. A random sample is more likely to be representative of the universe because random selection balances out both the known and unknown characteristics of a population. CES began moving toward implementing a probability sample in the early 1990s. At that time, probability sampling had been the statistical standard for nearly 50 years, but considerations such as cost, time, and a need to maintain historical time-series data had held CES back from implementing one.

The impetus for examining the feasibility of implementing a probability sample came from an unusually large benchmark revision⁸ in March 1991. Although sample design ultimately was not found to be the cause of this revision, a BLS-commissioned study by the American Statistical Association recommended a move to a probability sample. Following this study, the CES program began extensive research to develop a probability sample that would be both cost effective and technically rigorous. This research resulted in the gradual implementation of a CES probability sample, with wholesale trade being converted to it in June 2000, goods-producing industries in June 2001, and the remaining industries in June 2002.

Data collection

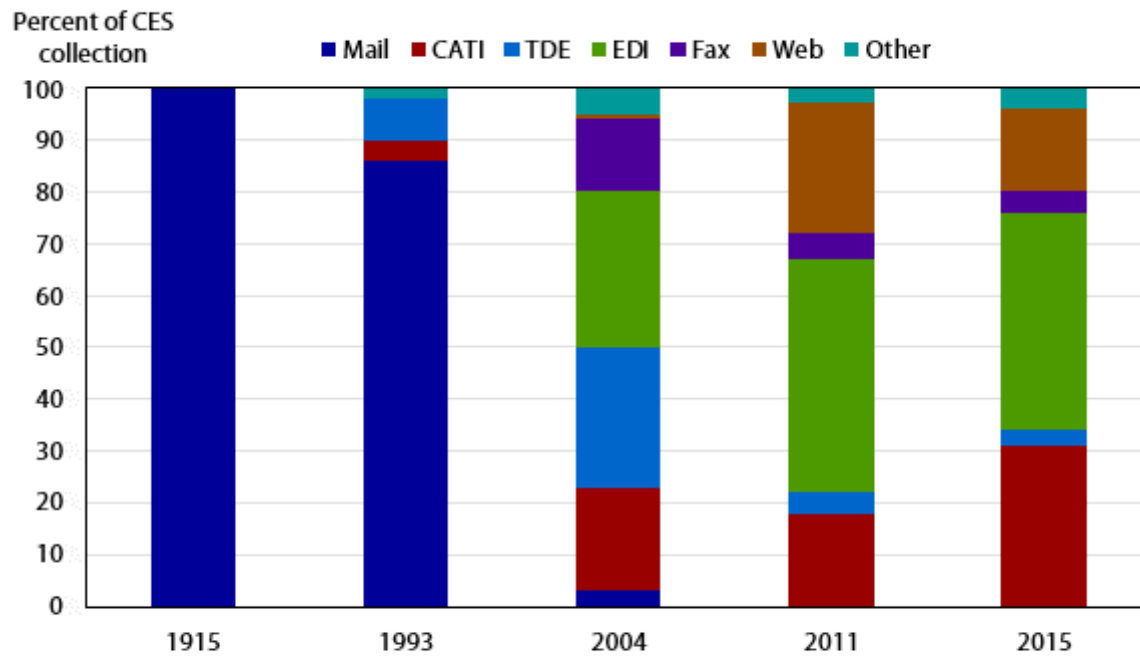
Initially, all CES data collection was done by postal mail, using monthly collection forms. In 1930, the CES survey adopted a 6-month “shuttle” collection form—so called because the form shuttled back and forth between CES and the respondent. In 1938, a 12-month shuttle form was introduced.

CES gradually evolved into a federal–state cooperative program, with cooperative agreements existing with all states by 1949. State workforce agencies (then known as state employment security agencies) eventually took over nearly all data collection. Using guidelines from CES, individual states also enrolled new establishments into the sample. Throughout the years, state workforce agencies became, and remain to this day, a vital part of the program. Although their explicit roles have evolved over the years, these agencies have adapted and continued to greatly affect CES.

State data collection predominated until the early 1990s, when BLS began to introduce new, electronic data collection methods that it had begun researching and testing during the 1980s. These electronic methods required specialized hardware and software infrastructures and, in many cases, were more cost effective in a centralized environment than in a decentralized setting requiring infrastructure in each state. The most prominent new collection methods included the following:

- Computer-assisted telephone interviewing (CATI), which provides prompting information and data capture to survey interviewers collecting data by phone.
- Touchtone data entry (TDE), in which survey respondents submit data through an automated telephone interview.
- Electronic data interchange (EDI), in which companies submit large payroll datasets, which are then processed to conform to CES reporting formats. (Currently, EDI is the most widely used data collection method.)
- Fax reporting, in which respondents submit a data collection form by fax.
- Web reporting, in which respondents use an online form to submit data.

Figure 2. CES data collection methods, 1915–2015



Note: The years shown represent major inflection points in the transition over time from mail to multimodal CES data collection.

Source: U.S. Bureau of Labor Statistics.

Changes in CES data collection methods over time are shown in figure 2.

Beginning in the mid-1990s, BLS gradually assumed responsibility for nearly all new sample enrollments and monthly collections. One important reason for this development was that states had low initial response rates, and it was essential to raise these rates in support of the upcoming move to a probability-based sample. There were also benefits in cost, efficiency, and reduced respondent burden in the newer, centralized data collection methods. This was especially true for EDI, which allowed large multistate firms to report all of their worksites in one file. However, despite the increased centralization of data collection, federal–state partnership has remained an important part of the CES program.

Over time, the CES collection forms also evolved to meet the changing needs of the program. Major changes to the forms included the following:

- Addition of all-employee hours and earnings: These long-sought-after data items were added to the form in a redesign completed in 2005.
- Addition of two pay groups: To improve the ease of collecting payroll and hours data, CES redesigned its form to allow each firm to report separately for two pay groups (e.g., production workers paid weekly and other staff paid biweekly). This change also simplified the process of normalization, in which all data are converted to a 1-week equivalence, and was critical to the success of the all-employee hours and earnings initiative.

- Inclusion of tips in the CES payroll definition: In 2007, CES began including tips in its payroll definition for the service-providing industries. (Historically, there had been some ambiguity around whether tips should be included or excluded.) On forms used before the addition of all-employee hours and earnings, the reporting of tips was requested only from wholesale and retail trade establishments.

As the CES survey gradually replaced mail collection with an array of electronic collection methods, the standard CES forms were adapted to be more compatible with the new methods. For example, the traditional collection form is no longer used in EDI collection; instead, respondents are provided a booklet with data items and definitions, along with the specifications for developing an electronic file for reporting CES data items.⁹

Benchmarking

In the late 1920s, Federal Reserve statisticians noted that, when compared with data from the biennial Census of Manufactures, CES data on manufacturing employment exhibited a downward bias. CES was urged to adjust, or “benchmark,” its data to the census data. The first such benchmark was completed and published in 1935, with employment data being republished for 1923–29. The revision was very large by modern standards, approximately 12 percent.

Another development in 1935 was the passage of the Social Security Act, which established the Unemployment Insurance (UI) program. Employers were required to regularly report employment and payroll data to the state employment security agencies. This reporting requirement provided a more timely, near-universe employment count that could be used in benchmarking, and CES adopted UI employment data as its primary benchmark source. In 1940, CES published its first UI-based benchmark for selected industries and, in 1949, the first comprehensive UI-based benchmark was completed and published. Newly expanded UI-based data made it possible to directly benchmark all levels of industry detail.

In 1982, CES began benchmarking every year, on a regular schedule, to a UI-based benchmark. This practice fulfilled one of the recommendations of the 1979 National Commission on Employment and Unemployment Statistics. Before that time, delays in UI data processing and occasional changes in UI coverage meant that benchmarks were released at different times of the year and, in some years, the benchmarking process was delayed and a multiyear revision released at a later time.

Between 1982 and 2004, the national benchmark revisions were released in June of each year, with one exception. In 1990, in order to complete a major SIC revision and historical reconstruction project, CES delayed the national benchmark release until September. Improvements in the speed of processing of UI data from the BLS Quarterly Census of Employment and Wages (QCEW)—previously known as ES-202—allowed CES to advance its publication date from June to February, beginning in 2004.

The CES program started to announce a preliminary benchmark revision in December 1991, when some users and media began predicting the size of the CES benchmark revisions on the basis of the release of preliminary first-quarter QCEW figures. Over time, the announcement was moved up—first to November, then to October—and currently is released in September. The earlier dates were made possible thanks to the speedier compilation of the QCEW data, which are the primary source for CES benchmarking. The timing of the September announcement now coincides with the BLS publication of the preliminary first-quarter QCEW data.¹⁰

Birth/death estimation

Because the CES sample is not continuously updated, there is an unavoidable lag between the time an establishment opens for business and the time it becomes available for sampling. Since new firm births generate a portion of employment growth each month, nonsampling methods must be used to estimate this growth.

Before CES implemented a probability sample, which was phased into production between June 2000 and June 2003, the program used a procedure known as “bias adjustment” to account for employment changes due to business births and deaths. However, this procedure attempted to correct for *all* sources of bias in the monthly sample-based estimates, not just the contribution of business births and deaths. Using “bias factors,” CES basically modeled the net difference between the historical CES and QCEW employment levels and projected that difference forward, in an attempt to minimize future CES benchmark revisions. The regular use of bias adjustment began in the mid-1970s.

Internal CES research culminating in the late 1990s showed that a key assumption in bias adjustment—the stability of QCEW–CES differences—did not hold consistently, especially when employment reached a turning point or a major change in trend. With the introduction of the new probability sample, CES had an opportunity to implement a new method of modeling the employment change resulting from business births and deaths.

CES has found that the relationship between business births and business deaths is fairly stable and largely offsetting. Employment change at failing establishments *is* captured by BLS, either through those establishments’ nonresponse or by BLS treating them as nonrespondents when they do respond. Because employment effects from business deaths are assumed to approximate those from business births, the noninclusion of business deaths is assumed—for the most part—to offset the employment effects of the birth of businesses that have not yet been included in the CES sample frame.

Employment losses from business deaths, however, are not *precisely* equal to gains from business births. Therefore, it is necessary to model the remaining, or residual, employment effects coming from business births. Birth/death modeling uses standard “autoregressive integrated moving average” (ARIMA) techniques, whose inputs are 5 years of QCEW data in which each establishment is classified as a continuing unit, a birth, or a death. Using this process, CES is able to develop an estimate of monthly employment change that accounts for business births. Net birth/death employment is added to sample-based, not-seasonally-adjusted estimates each month.¹¹

An important change to birth/death methodology occurred with the February 2011 release of January 2011 data. By that point, quicker availability of QCEW data had allowed for the quarterly forecasting of birth/death residuals, as opposed to the previous practice of annual forecasting. This change was intended to reduce revisions to the birth/death residuals.

Seasonal adjustment

CES data, like many time series, contain observable, regular seasonal fluctuations. Because these fluctuations can obscure trends in the data, it is often desirable to remove them.

In 1954, BLS began to prepare and publish seasonally adjusted estimates for the first time, using a technique known as the “standard ratio to moving average” technique. Before that time, seasonally adjusted data on industry

employment had been published by the Federal Reserve Board. In 1980, CES began to use the U.S. Census Bureau's X-11 ARIMA procedure¹² for seasonal adjustment of national series.

From 1980 through June 1989, CES national series were seasonally adjusted with the use of factors updated annually as part of the program's benchmarking process. From November 1989 through May 2003, these seasonal adjustment factors were updated semiannually. The change from annual to semiannual updating was made in order (1) to incorporate more current information, from the most recent sample-based estimates, into the seasonal adjustment factors and (2) to be consistent with the CPS national estimates for which the 6-month updating was already in place.

Also in the 1980s, CES introduced several special adjustments within its seasonal adjustment process, to correct for anomalies in the employment, hours, and earnings series. Most of these anomalies result from "calendar effects" in the not-seasonally-adjusted series. Calendar effects, often driven by the length of the time interval between observations, are recurring anomalies in time-series data that follow predictable patterns. Calendar effects distort the seasonally adjusted series and can result in false economic trend analysis. Examples of calendar effects are the variation in the interval (4 or 5 weeks) between survey reference periods, floating holidays such as Labor Day, and weather effects in the construction industry.¹³

In 1996, CES converted to the newly available X-12 ARIMA software in order to take advantage of new features that improved special adjustments for calendar effects and other anomalies.

In June 2003, simultaneously with the implementation of a major survey redesign, CES introduced a concurrent (i.e., monthly) recalculation of seasonal adjustment factors for national estimates, in order to incorporate the most up-to-date employment data into these factors. Research had shown that this recalculation would reduce revisions to estimates of seasonally adjusted over-the-month employment changes that occur with benchmark revisions.¹⁴

Before the introduction of concurrent seasonal adjustment for national series in June 2003, CES published the projected seasonal adjustment factors for future months as soon as they were produced. This practice began because, in the early days of seasonal adjustment, some users were concerned about the legitimacy of the seasonal adjustment process and sometimes even questioned whether the process was a method to "manipulate" the data. Publishing the factors ahead of time helped mitigate these concerns.

Conclusion

From its humble beginnings a century ago, the CES program has evolved into one of the world's most prominent statistical surveys. Starting with a modest release of employment and gross payroll data for four industries, drawn from a few states, CES has grown to cover the entire nonfarm economy, publishing a wide variety of data on employment, hours, and earnings. Ongoing quality improvements—such as benchmarking and birth/death modeling—have served to bolster confidence in the accuracy of CES data. At the 100-year mark, the CES program's accomplishments are many, but the important work of providing current, relevant data on the U.S. economy goes on, and CES has moved boldly into its next century.

SUGGESTED CITATION

John P. Mullins, "One hundred years of Current Employment Statistics—an overview of survey advancements," *Monthly Labor Review*, U.S. Bureau of Labor Statistics, August 2016, <https://doi.org/10.21916/mlr.2016.39>.

NOTES

- ¹ The Current Employment Statistics (CES) program, which provides detailed industry data on employment, hours, and earnings of workers on nonfarm payrolls, is a monthly survey of about 143,000 businesses and government agencies, representing approximately 588,000 individual worksites. For more information on the program's concepts and methodology, see "Technical notes for the Current Employment Statistics survey" (U.S. Bureau of Labor Statistics), <https://www.bls.gov/web/empsit/cestn.htm>. To access CES data, see "Current Employment Statistics—CES (national)" (U.S. Bureau of Labor Statistics), <https://www.bls.gov/ces>.
- ² Historical documentation for the CES program is incomplete. The author has pieced together the facts as accurately as possible, using limited CES historical documentation.
- ³ The North American Industry Classification System (NAICS) classifies establishments into industry groups on the basis of the similarity of their production processes. NAICS was collaboratively developed by agencies representing Canada, Mexico, and the United States. The use of common industry definitions facilitates economic comparisons and analysis among the three countries, and the production-oriented nature of the classification system maximizes the use of industrial statistics in the production of information on inputs and outputs, productivity, industrial performance, and other economic data.
- ⁴ Derivative series are data series derived from basic employment, hours, or earnings data. The average weekly earnings derivative series, for example, is the product of average weekly hours and average hourly earnings.
- ⁵ Probability sampling is the technique of randomly selecting a subset of a population, with the sample then being used to represent the entire population. The randomness of selection ensures that every individual has an equal chance of selection and, therefore, is representative of members of the population who are not selected.
- ⁶ "Analysis of BLS-790 sample with a proposal for a new sample design" (U.S. Bureau of Labor Statistics, June 1963).
- ⁷ Quota sampling is a nonprobability type of sampling in which a sample is chosen from specific, mutually exclusive subgroups on the basis of prespecified characteristics. Sample units are then selected from each subgroup. In the case of CES estimates, the subgroups were state, detailed industry group, and establishment size.
- ⁸ In the benchmarking process, sample-based CES estimates are reconciled with employment counts drawn primarily from state unemployment insurance (UI) records. Because about 98 percent of all U.S. employing businesses must pay UI premiums for their workers, these records provide a near-universe count of employment. Other sources are used for workers not covered by UI.
- ⁹ For a more detailed explanation of CES data collection, see "One hundred years of Current Employment Statistics data collection," *Monthly Labor Review*, January 2016, <https://www.bls.gov/opub/mlr/2016/article/one-hundred-years-of-current-employment-statistics-data-collection.htm>.
- ¹⁰ Detailed information on the CES benchmarking process can be found at <https://www.bls.gov/web/empsit/cestn.htm#section6b> and <https://www.bls.gov/ces/tables.htm#benchmark>.
- ¹¹ Detailed information on the CES birth/death model can be found at <https://www.bls.gov/web/empsit/cestn.htm#section5c> and <https://www.bls.gov/web/empsit/cesbd.htm>.
- ¹² For a description of the X-11 ARIMA procedure, see Julius Shiskin, Allan H. Young, and John C. Musgrave, "The X-11 variant of the Census Method II seasonal adjustment program," Technical Paper No. 15 (Bureau of the Census, February 1967), <https://www.census.gov/ts/papers/ShiskinYoungMusgrave1967.pdf>.
- ¹³ Detailed information on CES seasonal adjustment can be found at <https://www.bls.gov/web/empsit/cestn.htm#section5>.
- ¹⁴ "Concurrent seasonal adjustment for industry employment statistics" (U.S. Bureau of Labor Statistics, October 21, 2002), <https://www.bls.gov/ces/cescsapdf.pdf>.

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