Monetary Policy and Investment Dynamics: Evidence from Disaggregate Data

Gregory E. Givens[a,*], Robert R. Reed[a]

[a] *Department of Economics, Finance, and Legal Studies, University of Alabama, Tuscaloosa, AL 35487, USA*

First Draft: June 2015
This Draft: February 2018

Abstract

We use disaggregated data on the components of private fixed investment (PFI) to estimate industry-level responses of real investment and capital prices to unanticipated monetary policy. The response functions derive from a restricted large-scale VAR estimated over 1959-2017. Our results point to significant cross-sector heterogeneity in the behavior of PFI prices and quantities, which we interpret as evidence of widespread asymmetry in the monetary transmission mechanism. For capital assets belonging to the equipment category of fixed investment, we find that quantities rather than prices usually absorb most of the fallout from a policy innovation. By contrast, price effects tend to be higher and output effects lower for nonresidential structures.

Keywords: Investment, Monetary policy, Disaggregate data, VAR

JEL Classification: E22, E32, E52

*Corresponding author. Tel.: + 205 348 8961.
E-mail address: gegivens@cba.ua.edu (G.E. Givens).

1 Introduction

Conventional wisdom suggests that the speed and extent to which monetary policy influences real activity varies from one sector of the economy to another. An understanding of the mechanisms responsible for these differences is fundamental to the practice of central banking and explains why the impetus for policy intervention often depends on the particular source of weakness or instability in the market. For example, in an effort to justify further stimulus in early 2001, Federal Reserve officials noted at the time that the current downturn was partly a consequence of flagging private expenditures on capital equipment. The press release following the January 31, 2001 meeting of the Federal Open Market Committee (FOMC) stressed that "business spending on capital equipment [had] weakened appreciably" and that "circumstances [had] called for a rapid and forceful response of monetary policy." The recession of 2007-2009, on the other hand, was greatly intensified by a collapse in residential investment. Policy statements published after the April 30, 2008 FOMC meeting, in which the target federal funds rate was lowered to two percent, acknowledged that "the deepening housing contraction [was] likely to weigh on economic growth over the next few quarters."

Given the status that capital and investment-related activity have in FOMC deliberations, and in recognition of our need to better understand the sectoral effects of policy, this paper empirically examines how conditions across all of the private fixed investment categories reported by the Bureau of Economic Analysis (BEA) respond to aggregate monetary shocks. To date, there are 67 distinct fixed investment types represented in the disaggregated data that underlie the National Income and Product Accounts (NIPA). Examples include commercial warehouses, lodgings, mining and oilfield machinery, railroad equipment, medical instruments, and single-family housing. For each industry group, the BEA publishes quarterly data on both nominal expenditures and the price level. Our main goal here is to document potential cross-sector differences in the response of these series to unanticipated monetary policy. The results help clarify aspects of the transmission mechanism as it pertains to the many diverse capital-goods producing industries within the US economy.

Our focus on disaggregated data has two advantages over traditional time-series discussions of investment that rely on aggregate data alone. First, basic neoclassical models of investment demand (e.g., Jorgenson, 1963; Hall and Jorgenson, 1967) predict that the real effects of policy operate through the user cost of capital.[1] Among the known determinants of

[1]Closely related to the user-cost approach is the q-theory framework originally developed by Tobin (1969). Formal links between the two rely on the presence of dynamic adjustment costs and were first incorporated into investment models by Abel (1980), Hayashi (1982), and Summers (1981).

user cost is the relative price of investment, which owing to external factors like the elasticity of capital supply, may respond differently to monetary shocks depending on the industry or type of capital in question (e.g., Goolsbee, 1998). If true, then such shocks could have non-trivial *distributional* effects as user costs vary and resources get reallocated across sectors. Of course verifying whether policy generates capital reallocation in the short run requires scrutiny of the cross-sectional variation present in industry-level data.

A second benefit of disaggregated data is that it allows one to search for relationships among price and quantity dynamics *within* and *across* more broadly-defined asset groups. Here we have in mind categories that encompass multiple industries, namely, residential structures, nonresidential structures, durable equipment, and intellectual property. Sorting the cross-sectional results in this way provides insight on whether, or to what extent, activity within related industries react similarly to monetary shocks. But at the same time, it also draws attention to the contrast in capital market dynamics across industry groups that produce very different investment products. Both comparisons are important, particularly since efforts to identify policy effects using aggregate investment data have demonstrated such limited success (e.g., Blanchard, 1986; Bernanke and Gertler, 1995).

The notion that monetary policy affects various sectors differently is not new. There is a large body of research that studies the impact of policy disturbances on a wide range of disaggregated prices and quantities, and the results overwhelmingly point to sizable and significant cross-sector heterogeneity. Lastrapes (2006) and Balke and Wynne (2007) demonstrate that policy shocks alter the distribution of prices comprising the numerous industry components of the Producer Price Index. The authors interpret these relative price movements as confirmation of important monetary nonneutralities. Bils, Klenow, and Kryvtsov (2003) and Altissimo, Mojon, and Zaffaroni (2009) draw similar conclusions for the major retail price categories found in the US and euro area Consumer Price Index, respectively. In a related set of papers, Clark (2006), Boivin, Giannoni, and Mihov (2009), and Baumeister, Liu, and Mumtaz (2013) use disaggregate data on personal consumption expenditures to assess differences between aggregate and sectoral inflation dynamics. Using industry-level data, Barth and Ramey (2002), Dedola and Lippi (2005), and Loo and Lastrapes (1998) report substantial heterogeneity in sectoral output responses to a monetary shock.

Despite the many contributions that deal with the distributional effects of monetary policy, the literature is largely silent on whether such effects take hold in markets for physical capital. This is puzzling considering that investment is a major source of economic activity and an integral component of the policy transmission channel central to models of the business cycle. Nevertheless, existing studies mostly focus on aggregate investment and leave out information contained in disaggregate data (e.g., Bernanke and Gertler, 1995; Christiano, Eichenbaum, and Evans, 1999). Our paper aims to fill this void, and by doing so, contributes to the policy discussion in two ways. First, to stabilize the economy central banks must know how their actions affect conditions across the full spectrum of capital-producing industries. Our results inform policymakers by exposing the differences and similarities in the response to a monetary shock among all the investment categories represented in the NIPA. Second, the stylized facts that emerge from this study can serve as benchmarks for developing and evaluating more comprehensive models of the monetary transmission mechanism.

To obtain industry-level responses, we employ a structural vector autoregression (VAR) and identify monetary shocks as orthogonalized innovations to the federal funds rate. Concerns about degrees of freedom, however, mean that structural VARs typically involve only a limited number of economic variables. Incorporating a broad panel of disaggregated investment data would violate this practice and, absent restrictions on the model, make estimation infeasible for any suitable lag choice.

In this paper we avoid problems associated with large-scale VARs by adopting an empirical strategy used by Loo and Lastrapes (1998), Barth and Ramey (2002), Lastrapes (2006), and Balke and Wynne (2007) and formalized in Lastrapes (2005). The procedure calls for partitioning the system into two blocks, the first containing macroeconomic aggregates or 'common factors' and the second containing industry variables. Degrees of freedom are preserved by assuming (*i*) common factors are independent of industry-specific shocks and (*ii*) variables in the latter block are mutually independent after conditioning on the former. Under these conditions least squares is efficient and policy innovations can be identified in the usual way through restrictions on just the macro-variable equations.

Our baseline estimates reveal that the effects of policy are not uniform across capital-producing industries. While most, but not all, prices and quantities increase after a negative funds rate innovation, there is significant variation in the size and speed of the adjustment paths. These results also show up in auxiliary estimations that alter the sample period and relax the independence assumptions described above. Thus monetary policy appears to have robust distributional effects that stem from asymmetries in the transmission mechanism. This feature enables policy to affect the sectoral composition of fixed investment in the short run as well as the degree of dispersion in capital-goods prices.

While the full set of responses display considerable heterogeneity, isolating certain industry groups reveals some compelling similarities in the way investment prices and quantities interact. Notably, monetary policy appears capable of boosting real activity among makers of durable equipment. Estimates show that where production volumes respond swiftly, equipment prices often react sluggishly. By contrast, in markets for residential structures, shocks translate quickly into both higher prices and higher quantities. Where policy seems least effective in motivating capital formation is in nonresidential structures. Our results indicate that sellers usually raise prices in the short run rather than adjust quantities.

Having documented the industry responses, we go on to propose a simple demand-and-supply interpretation of the contrast in the price-quantity dynamics described above. In short, we attribute variation in the responses to sectoral differences in the elasticity of capital supply. Support for the idea comes from an analysis of industry data on gross profit rates. As a measure of market power, gross profits should correlate with the supply elasticity and thus may be useful for explaining how demand shocks get transmitted into prices versus quantities. When matched to our disaggregate responses, we find that equipment-producing industries tend to have lower profits than those in nonresidential structures. Such evidence points to flatter capital supply curves in the former and may well explain why the quantity effects are usually bigger and the price effects smaller after a monetary shock.

2 Investment Data

Source data for private fixed investment (PFI) come from the Underlying Detail Tables for Gross Domestic Product.[2] The tables separate PFI into components, the number of which differ by aggregation level. There are two components listed at the highest level, residential and nonresidential investment. The former comprises structures and equipment while the latter consists of nonresidential structures, business equipment, and intellectual property.

Fig. 1 illustrates the composition of PFI in the 1970s, 1980s, 1990s, and 2000s. To be clear, what it shows is the value of each component expressed *as a percentage* of total PFI averaged over a particular decade. So from the 1970s through the 1980s, for example, the biggest shift in the composition of PFI was an increase in the share of intellectual property and a decrease in the share of residential structures. By contrast, during the 1990s it was nonresidential structures that witnessed the largest declines. Through the 2000s spending on intellectual property continued to rise while the share of business equipment dropped.

[2]PFI measures spending by private businesses, nonprofit institutions, and households on fixed assets that are used in the production of goods and services in the US economy. The Underlying Detail Tables can be found at http://www.bea.gov/iTable/index_UD.cfm/

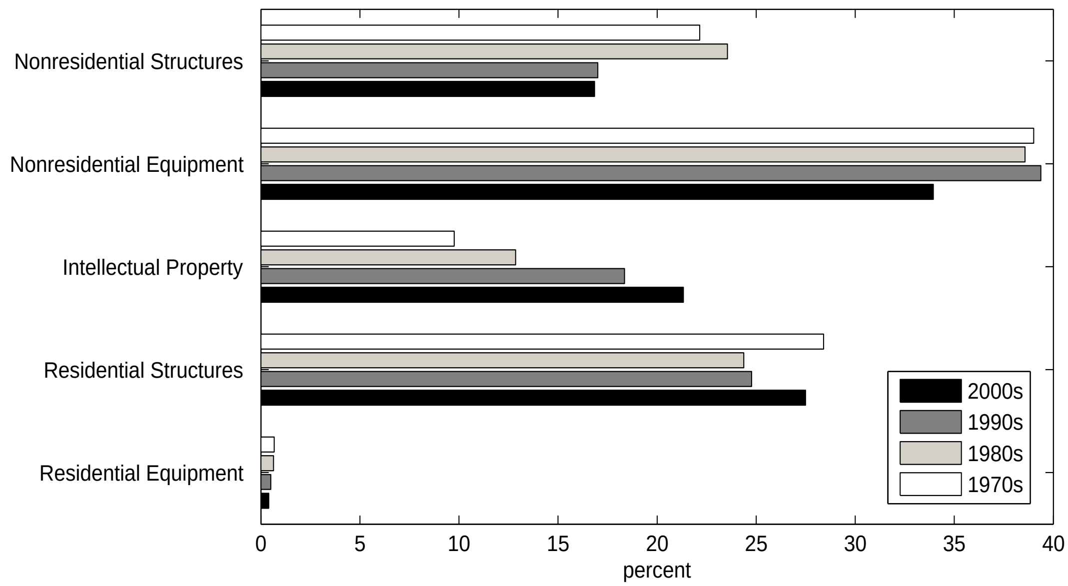

Fig. 1. BEA estimates of average annual nominal spending on nonresidential structures, nonresidential equipment, intellectual property products, residential structures, and residential equipment as a fraction (percent) of total private fixed investment are graphed for 1970-1979, 1980-1989, 1990-1999, and 2000-2009. Bars from each decade sum to 100.

The underlying data decompose PFI further into 16 subcategories covering more narrowly-defined asset classes. This third level of aggregation includes series such as commercial and health care buildings, information processing equipment, software, and permanent-site residential structures. Sinking even further in the detailed NIPA estimates reveals as many as 67 individual series spanning all of PFI. They represent the most disaggregate measures available, and most summarize investment activity within a specific industry. Examples include food and beverage establishments, warehouses, religious structures, photocopy equipment, fabricated metal products, farm tractors, and dormitories.

The exercises carried out in this paper employ a balanced panel of investment data assembled at the most detailed aggregation level published by the BEA. In most cases, quarterly data are available as far back as 1959. A small number of series, however, were excluded due to missing observations. In such instances, the series was replaced by data from the next lowest aggregation level.[3] This left us with a total of 64 disaggregate series on PFI prices and an equal number on nominal expenditures.[4]

[3]Separate data on light trucks, including utility vehicles, and other trucks, buses, and truck trailers are not available before 1987. We therefore replace these series with data on trucks, buses, and truck trailers, which appear without interruption from 1959 on.

[4]The BEA does not compute price indexes for net purchases of used residential or nonresidential struc-

3 Empirical Framework

We estimate the effects of an exogenous monetary shock on the cross-sectional variation of investment prices and real investment spending. In the tradition of Bernanke and Blinder (1992), we use a VAR and identify monetary shocks as innovations to the federal funds rate.

One complication that emerges is the large dimensionality of a VAR that includes, among other variables, 128 different PFI prices and quantities. Without placing over-identifying restrictions on the model, insufficient observations and a loss of degrees of freedom make estimation infeasible. To sidestep this problem, we adopt the strategy employed by Loo and Lastrapes (1998), Barth and Ramey (2002), Lastrapes (2006), and Balke and Wynne (2007). The procedure starts by partitioning the variables into two blocks. The first block consists of macroeconomic aggregates or 'common factors' that appear regularly in the VAR literature. This block includes real gross domestic product (GDP), the GDP chain-type price index (P), total private fixed investment (PFI), the deflator for private fixed investment (Q), the ratio of fuels and related products to finished goods in the Producer Price Index (FUEL), the effective federal funds rate (FFR), and the M1 money stock (M1). The second block consists of just two variables, one for the disaggregate price series of interest and the other for its corresponding real quantity. Separate (9-variable) VARs are then estimated for each of the 64 capital-producing industries represented in the underlying data.[5]

To preserve degrees of freedom we impose exclusion restrictions on the coefficients in the macro-variable equations that govern feedback from the disaggregate series. As explained by Lastrapes (2005), this type of 'block exogeneity' assumption implies that common factors are independent of industry-level prices and quantities. While restrictive, such an assumption is consistent with the view that industries are small relative to the overall economy or, alternatively, that the aggregate net effect of industry-specific shocks sums to zero on average.

The relationship between aggregate and industry variables can be seen more clearly by considering the VAR process

$$Z_t = \mu + A(L)Z_{t-1} + \epsilon_t, \tag{1}$$

where $Z_t' = [\mathrm{GDP}_t\ \mathrm{P}_t\ \mathrm{PFI}_t\ \mathrm{Q}_t\ \mathrm{FUEL}_t\ \mathrm{FFR}_t\ \mathrm{M1}_t\ \mathrm{i}_{j,t}\ \mathrm{q}_{j,t}]$, μ is a vector of constants, $A(L)$ is a conformable lag polynomial of order four, and the error term $\epsilon_t \sim$ i.i.d. $(0, \Omega)$. The quantities $\mathrm{i}_{j,t}$ and $\mathrm{q}_{j,t}$ denote total real spending and the price deflator, respectively, on investment goods from industry j. Independence of the first seven variables from $\mathrm{i}_{j,t}$ and $\mathrm{q}_{j,t}$

tures. Both quantities are therefore excluded from the panel.

[5]All series except FFR_t are expressed in natural-log levels. Real investment spending on goods from industry j is the ratio of nominal expenditures to the industry price index described in the last section.

is obtained by imposing restrictions on the lag polynomial of the form

$$\underset{9\times 9}{A}(k)=\begin{bmatrix} \underset{7\times 7}{A_{1,1}(k)} & \underset{7\times 2}{0} \\ \underset{2\times 7}{A_{2,1}(k)} & \underset{2\times 2}{A_{2,2}(k)} \end{bmatrix}$$

for all k lags. This gives (1) a fully block recursive structure.

Another benefit of setting $A_{1,2}(k) = 0$ is that it ensures consistent identification of FFR shocks across industries. If instead we left $A_{1,2}(k)$ unrestricted, then the shocks would vary with each price-quantity pair considered. Nevertheless, in section 5 we relax this assumption by re-estimating separate VARs for each industry while keeping $A_{1,2}(k)$ free. This allows industry variables to potentially influence the dynamics of the common factors, but with the drawback that policy shocks will not be the same across regressions.[6]

The second set of restrictions described by Lastrapes (2006) follows from assuming that industry dynamics are mutually independent after conditioning on the common factors. In other words, the correlation between prices and quantities across industries is fully explained by their joint dependence on the macro variables. In practice this is accomplished by including only one ($\mathrm{i}_{j,t}$, $\mathrm{q}_{j,t}$) pair at a time. Had we expanded Z_t to consider all industries together, mutual independence would impose a block-diagonal structure on $A_{2,2}(k)$ (a 128×128 object in this case) for all k lags. That is to say, each pair of ($\mathrm{i}_{j,t}$, $\mathrm{q}_{j,t}$) equations would contain just its own lags as well as lags of the common factors. This is equivalent to estimating our 9-variable system separately for each industry while leaving $A_{2,2}(k)$ unrestricted.[7]

We should point out that diagonal restrictions are valid insofar as the common factors can account for the sectoral co-movement of PFI prices and quantities. Whether our macro variables meet this standard is an open question, and the answer could have consequences for estimation. As a result, in section 5 we relax the mutual independence assumption by conditioning the VAR on the full panel of PFI data simultaneously using factor analysis. Augmenting the model with estimated factors allows policy shocks to generate correlation across industries that cannot be explained by their joint dependence on the macro variables.

We now turn to the identification of monetary shocks. Following the recursiveness approach described in Christiano *et al.* (1999), we specify a relationship between structural disturbances (ν_t) and reduced-form errors (ϵ_t) of the form $\epsilon_t = S\nu_t$, where S is a 9×9

[6]Examples of this approach include Carlino and Defina (1998) and Dedola and Lippi (2005).

[7]Using similar restrictions to estimate sectoral responses to oil shocks, Davis and Haltiwanger (2001) argue that the resultant system is equivalent to a pseudo-panel-data VAR.

contemporaneous matrix. It follows that (1) can be written in terms of structural shocks as

$$Z_t = B(L)\left(\mu + S\nu_t\right), \tag{2}$$

where $B(L) \equiv (I - A(L)L)^{-1}$ is a convergent infinite-order lag polynomial. Monetary shocks are interpreted as structural innovations to the federal funds rate, corresponding to the sixth element of ν_t in the transformed system (2). The impulse responses of Z_t to a policy shock are summarized by the matrix polynomial $B(L)S$.

The elements of $B(L)$ and S are estimated in two steps. First, we use ordinary least squares on (1) to obtain estimates of $A(L)$ and ϵ_t. We then impose orthogonality and normalization (unit variance) restrictions on the covariance matrix of ν_t along with triangular restrictions on the matrix S.[8] This allows us to identify S from a standard Choleski decomposition of Ω. Given estimates of $A(L)$, estimates of $B(L)$ are derived from $B(L) = (I - A(L)L)^{-1}$.

Our data set spans 1959:Q1 to 2017:Q3. These dates were chosen to maximize the sample length and hence degrees of freedom. Still, there are two potential concerns from employing such a long sample. First, a large amount of instability has been documented over this period resulting from shifts in policy behavior and macroeconomic volatility. So in section 5 we see how well our estimates hold up when conditioned on a subsample that displays less instability of this sort. Two, incorporating the period between 2009:Q1 and 2015:Q2 means that estimates could be distorted by non-linearities induced by the effective lower bound on the federal funds rate. We therefore spliced the funds rate data during these years with observations on the so-called 'shadow policy rate' estimated by Wu and Xia (2016).[9]

4 Empirical Findings

4.1 Aggregate Responses to a Policy Shock

Before commenting on the industry response functions, we verify that our estimated VAR generates aggregate dynamics consistent with known findings. Fig. 2 plots impulse responses for GDP_t, P_t, FFR_t, and $\mathrm{M1}_t$ to a one standard deviation (71 basis point) drop in the federal

[8] Imposing a lower triangular structure on S is motivated by standard assumptions regarding time lags in the transmission of monetary policy to the broader economy.

[9] As explained by the authors, the shadow rate accurately describes the stance of US monetary policy during and in the aftermath of the financial crisis when the actual funds rate was pegged near zero.

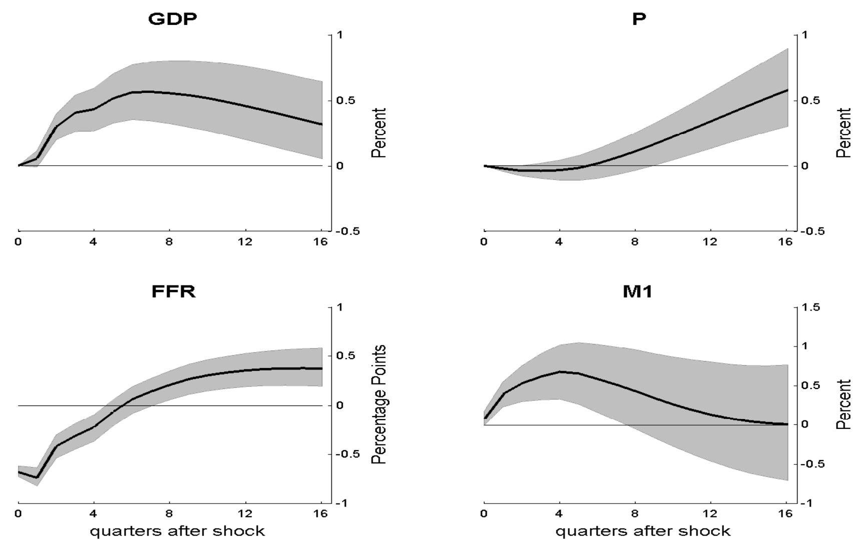

Fig. 2. Impulse responses to a (71 basis point) drop in the federal funds rate are graphed for: **GDP** - real GDP, **P** - GDP chain-type price index, **FFR** - federal funds rate, and **M1** - M1 money stock. Shaded regions are 90-percent confidence bands.

funds rate. Shaded regions correspond to 90-percent confidence bands.[10]

The effects of an expansionary FFR innovation can be summarized as follows. First, there is a persistent decline in the funds rate accompanied by a large and persistent increase in the money supply. Second, real GDP exhibits the usual hump-shaped pattern seen in numerous studies (e.g., Leeper, Sims, and Zha, 1996). We find that it reaches a peak of 0.6 percent seven quarters after the shock. Third, after a delay of five quarters, the GDP price index starts climbing to a permanently higher level. Four years after the shock, however, it is still only 0.6 percent above the baseline. Results showing aggregate prices responding sluggishly to a policy shock appear frequently in the literature (e.g., Christiano *et al.*, 1999). Notice that there is also little evidence of a "price puzzle," the counterintuitive finding that expansionary policy decreases the price level (e.g., Sims, 1992). Although P_t does fall slightly during the first year, the declines are not statistically different from zero.

[10]We take the joint distribution of the VAR coefficients and residual covariance matrix to be asymptotically normal with mean equal to the sample estimates and covariance equal to the sample covariance matrix of those estimates. We then draw $10,000$ random vectors from this normal distribution and, preserving identification restrictions, compute impulse response functions for each draw. Confidence bands correspond to the 5^{th} and 95^{th}-percent bounds of the simulated distribution of impulse responses over all $10,000$ trials.

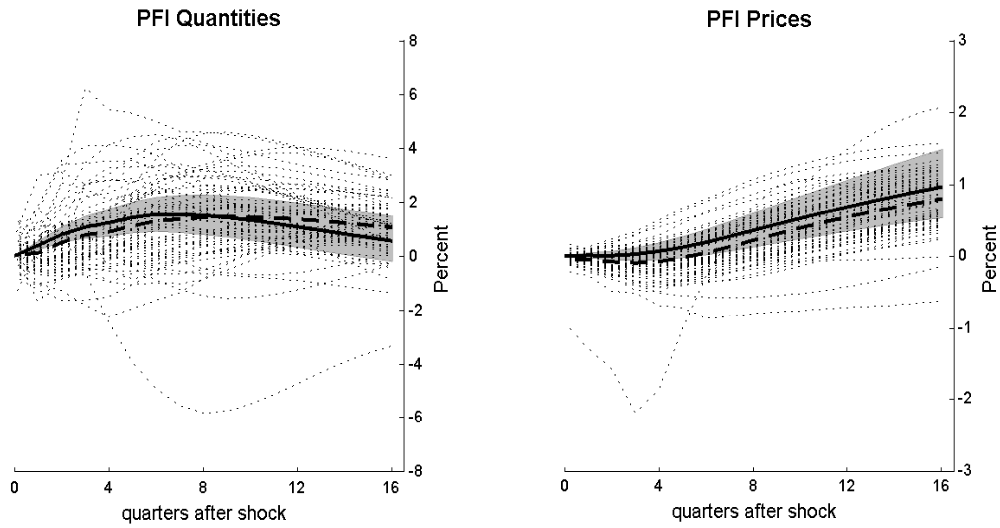

Fig. 3. Impulse responses to a (71 basis point) drop in the federal funds rate are graphed for PFI quantities (left panel) and prices (right panel). Dashed lines are unweighted averages across all industries. Solid lines are the responses of PFI_t and Q_t. Shaded regions are 90-percent confidence bands for the aggregate response functions.

4.2 Disaggregate Responses to a Policy Shock

In this section we analyze the responses of our disaggregate investment series to an unexpected drop in the funds rate. The discussion focuses on industry-level movements in both the price level and the quantity of real spending.

Fig. 3 plots the price and quantity responses for each industry. Solid lines are the responses of total private fixed investment, PFI_t, and its deflator, Q_t. Both variables belong to the macro-equation block of (1) and are assumed to be unaffected by policy in the initial period. Dashed lines are unweighted averages of the responses across industries.

There is considerable variation in the way industries react to a policy expansion. Differences emerge not only in the magnitude of the adjustment paths, but also in the direction. Regarding investment quantities, we find that a substantial portion (22 percent) respond negatively four quarters after the shock. In the majority of cases, however, the effects are positive, and as a result, the mean response at the one-year mark is 0.9 percent. Results also show most of the disaggregate quantities taking on the familiar hump-shaped profile seen in the aggregate data. Despite these similarities, we observe significant heterogeneity in the amplitude of responses. Over half peak between 0 and 2 percent while another fifth reach highs of 3 to 6 percent. Thus the real effects of policy appear robust in some industries but relatively weak in others. This finding supports the view that the strength of the transmission channel varies from one capital-goods sector to another.

By comparison, there is less sectoral heterogeneity in the response of investment prices. For the first few quarters after a shock, most PFI prices are not far from their baseline values. In fact, it takes over a year for the average price level to start rising. After a period of four years, however, all but three industries experience some inflation, and a majority (three-fourths) sustain anywhere from 0.5 to 1.5 percent.

We should point out that while expansionary shocks lift investment prices in the long run, a considerable fraction display a price puzzle in the short run. To be precise, 58 percent of all industries witness a decline in prices after one year. Still these discounts are small, averaging less than 0.3 percent. After two years, the share of industries experiencing lower prices is only 27 percent. That number falls to just 5 percent by the three-year mark.

Another way to focus attention on the heterogeneity present in Fig. 3 is by assembling the full cross-sectional distribution of prices and quantities at various horizons. To that end, Fig. 4 plots smoothed estimates of the probability density functions for the responses one, two, three, and four years after the onset of a shock.[11] Comparing densities across horizons shows how the distributional effects of a policy shock change with the passage of time.

Looking across all categories of fixed investment, we see that the dispersion in quantities is greater than the dispersion in prices at each horizon. The variance of PFI quantities peaks after eight quarters, at which time over half of all industries have boosted sales by at least 1.5 percent and a few by as much as 4 percent. Beyond that point, the variance narrows. Interestingly, the behavior of the first and second moments are similar in this case. Notice that the mean shifts right for the first two years (0.9 to 1.4) and then shifts left in years three and four (1.4 to 1.0). Thus both moments could be said to exhibit hump-shaped dynamics.

Monetary policy clearly has a more enduring effect on the mean and variance of PFI prices. Consistent with Fig. 3, we see that the average price response increases each year as the distribution repeatedly shifts towards the right. The variances, however, tend to level off after about three years. Standard deviations computed from each density are around 0.3 for the first two years and 0.4 for years three and four (see also Table 1).

Whether price and quantity dispersion is a compelling feature of the data depends on the significance of our point estimates. To assess significance, we follow Balke and Wynne (2007) by recording the fraction of responses that are statistically different from zero at a 10-percent level. Results are shown in the left panel of Fig. 5. At horizons of two quarters or less, the fraction of significant quantity responses never exceeds 30 percent. The proportion tops

[11] We use a non-parametric kernel estimator to obtain smoothed values of the density functions. The bandwidth for each density is optimal under the assumption that the target distribution is Gaussian.

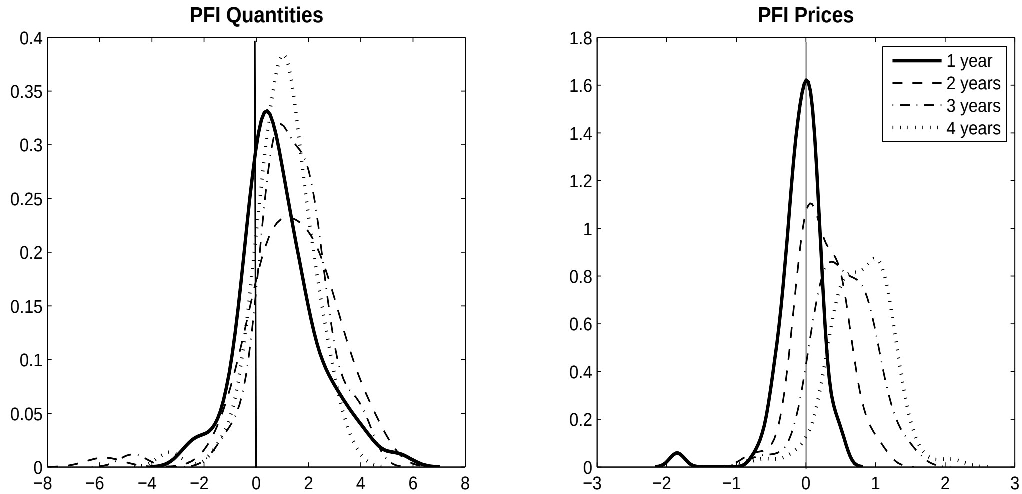

Fig. 4. Smoothed estimates of the density functions for PFI price (right panel) and quantity (left panel) responses to a (71 basis point) drop in the federal funds rate are graphed for 1, 2, 3, and 4-year horizons.

out at 53 percent seven quarters after the shock and reverts to 25 percent by the four-year mark. Regarding prices, barely 17 percent are significant after one quarter, but 44 percent are significant six quarters later. By the end of the fourth year, 83 percent are statistically different from pre-shock levels.

It is possible that the disparate effects of a policy shock are due to sampling error when in fact the true population dynamics are homogeneous. To assess the likelihood of this scenario, we simulate the industry variables using a bootstrap procedure discussed in Lastrapes (2006). After estimating (1), we draw a bootstrap sample of residuals corresponding to $[\mathrm{i}_{j,t}\ \mathrm{q}_{j,t}]'$ for each industry. The sample is then used to simulate a new series for $[\mathrm{i}_{j,t}\ \mathrm{q}_{j,t}]'$ that equals the bootstrapped residuals plus (scaled) observations of PFI_t and Q_t. As explained in Lastrapes (2006), the simulated series reflects the null hypothesis that aggregate and industry dynamics are different only by an error term. We then re-estimate the VAR with simulated data and obtain impulse responses using the same identification strategy discussed in section 3. We replicate this experiment 500 times and record the standard deviation of prices and quantities at each pass. The right panel of Fig. 5 plots the average standard deviations across replications along with the actual standard deviations implied by the benchmark estimation. If the distributional effects of a policy shock are merely a consequence of sampling error, then the estimated and simulated moments will not be far apart.

The dispersion in prices and quantities is not likely the result of sampling error alone. While the simulated responses do exhibit some cross-sectional variability, the average amount

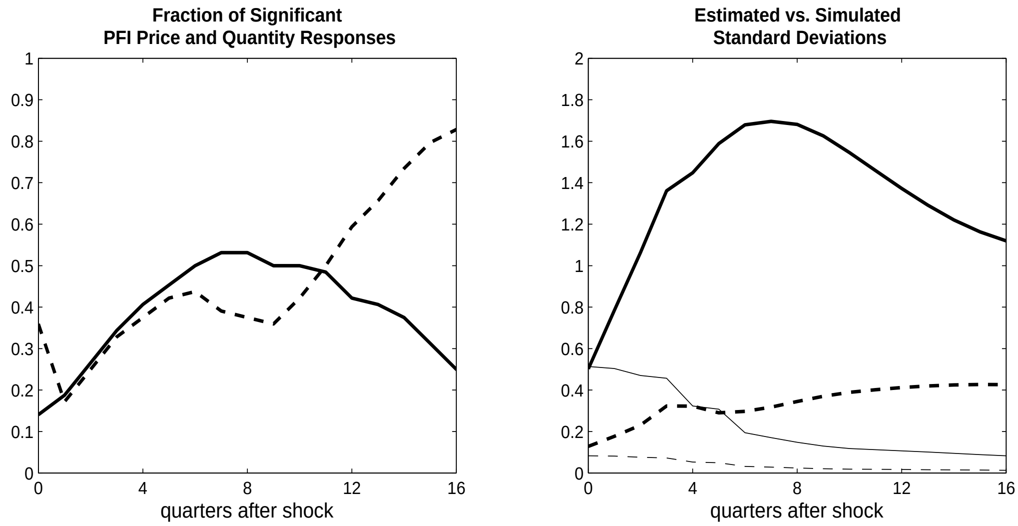

Fig. 5. The left panel shows the fraction of all PFI prices (dashed line) and quantities (solid line) in which the response to a monetary policy shock is significantly different from zero at a 10-percent level. The shock is an unexpected decrease of 71 basis points to the federal funds rate. The right panel shows the standard deviation of the price (dashed lines) and quantity (solid lines) responses across all industries under the benchmark estimation (thick lines) along with the *mean* standard deviations (thin lines) computed over bootstrap simulations of a model that assumes uniform price and quantity responses.

is relatively small and approaches zero a few years after the shock. For example, after four years the standard deviation of the estimated quantity responses is 100 basis points higher than the mean standard deviation of simulated quantities. The corresponding difference for price dispersion is about 40 basis points. Possibly the only horizons at which one would not reject the null is the impact period and the following quarter. Thus it stands to reason that the apparent distributional effects of policy are being driven, not by sampling error, but by widespread changes in relative prices and quantities. We interpret these changes as evidence of sectoral asymmetry in the transmission of monetary policy to fixed-capital formation.

4.3 Major Components of Fixed Investment

Estimates show that prices and quantities generally increase in the years after an unexpected drop in the funds rate. Yet they also point to considerable variation across industries in the timing and magnitude of these effects. In some industries output adjusts rapidly, while in others it is the price level that is most affected. A natural question then is whether there are any patterns or tendencies in the way investment prices and quantities interact over time.

To answer this question, we organize the sectoral responses into four categories: non-residential structures, residential structures, durable equipment, and intellectual property products. Fig. 6 sorts the response functions into these groups, and Fig. 7 plots the fraction

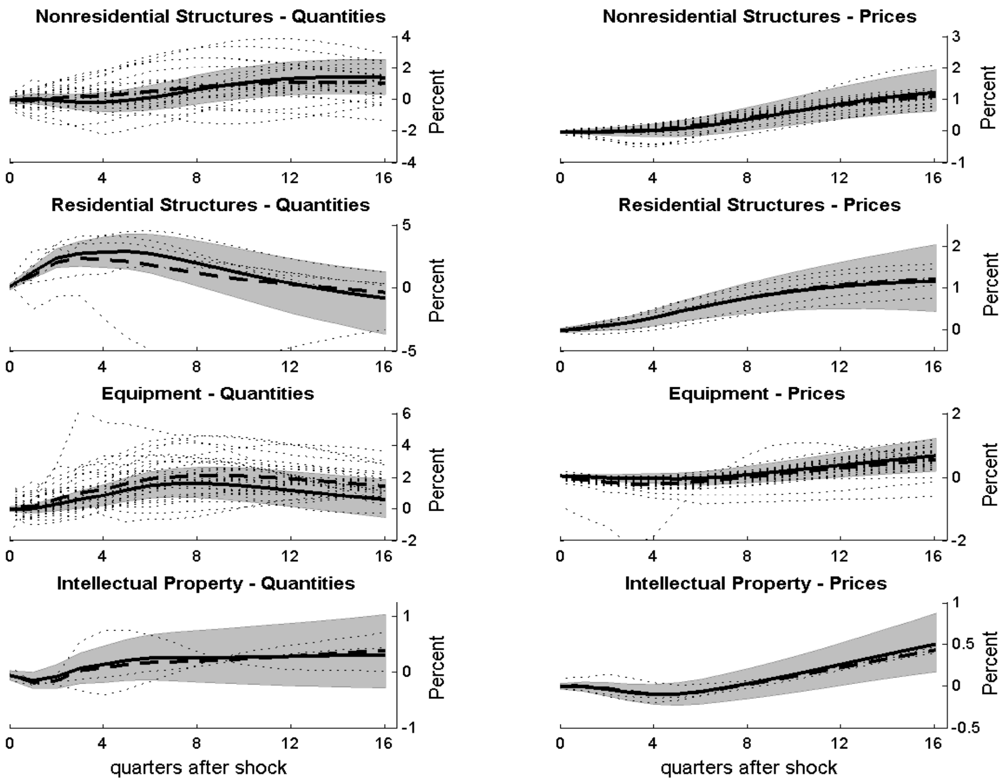

Fig. 6. Impulse responses to a (71 basis point) drop in the federal funds rate for PFI quantities (left panel) and prices (right panel) are sorted by nonresidential structures, residential structures, equipment, and intellectual property. Dashed lines are unweighted averages over industries in a given category. Solid lines are the responses of the aggregate quantity and price index. Shaded regions are 90-percent confidence bands for the aggregate response functions.

within each one that are significant at a 10-percent level.

Within nonresidential structures, we see substantial variation in the quantity responses to a funds rate shock. After a year, roughly one-third are negative, with some falling by as much as 2 percent. Though most tend to rise over time, it is clear that the dispersion persists beyond one year. As a result, the mean response is quite small. It tops out at 1.1 percent by the end of year three, but at this point, just 25 percent are statistically significant as seen in Fig. 7. Thus in the majority of cases, policy appears to have limited ability to increase real spending on nonresidential structures at normal business cycle frequencies.

The behavior of prices is very different. As reported in Table 1 (second panel), the median price response after twelve quarters is 0.8 percent, compared to 0.5 percent when accounting for all of PFI. What's more, 19 of the 23 industry responses are statistically significant at this point (Fig. 7). It is also worth noting that the standard deviation of prices for

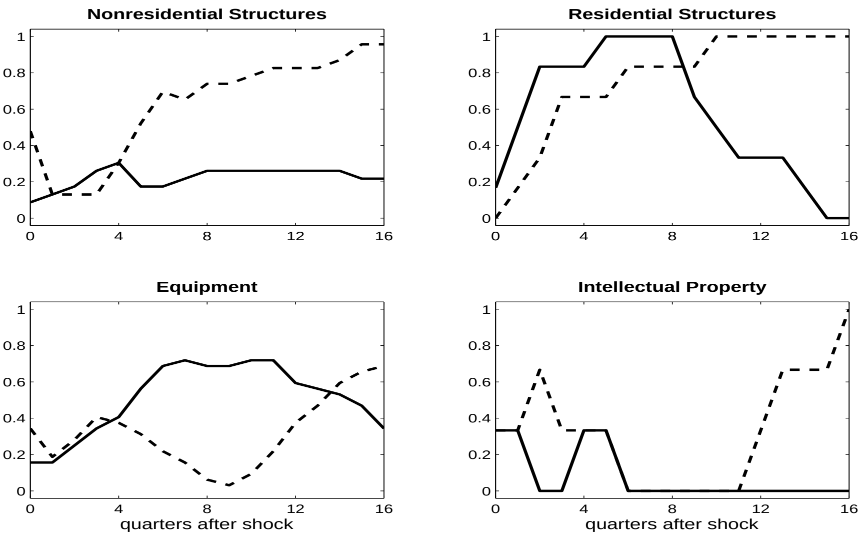

Fig. 7. For nonresidential structures, residential structures, equipment, and intellectual property, the fraction of industry prices (dashed lines) and quantities (solid lines) in which the response to a policy shock is statistically significant at a 10-percent level are graphed for horizons up to four years. The shock is an unexpected decrease of 71 basis points to the federal funds rate.

nonresidential structures is smaller than the standard deviation for all price components of PFI. This implies that the dispersion across all industries is being driven by dispersion elsewhere in the economy or by discrepancies in the average price dynamics between the four major investment categories. Both of these explanations turn out to be consistent with the disaggregate data as shown below.

Differences between prices and quantities are perhaps even more visible in the equipment-producing industries. But here it is the real margin that is typically more elastic. Estimates show most of the quantity responses peaking around eight quarters, with 70 percent statistically significant according to Fig. 7. As seen in Table 1 (fourth panel), the median response at this horizon is three times the median response for nonresidential structures. Equipment prices, on the other hand, are generally slow to adjust. Two years elapse before average prices respond positively to a drop in the funds rate. Even after three years, fewer than 40 percent are statistically different from zero. Thus in the short run, expansionary policy can, for the most part, boost real spending on equipment while keeping prices subdued.

Whether the contrast in the dynamics of structures and equipment should be viewed as a key feature of the policy transmission mechanism depends on the role of monetary shocks as a source of industry fluctuations. In what follows we calculate their contribution to the forecast error variances of each PFI price and quantity series at horizons between one and

Table 1
Descriptive statistics for the distribution of PFI price and quantity responses

	Quantity responses (in percent)				Price responses (in percent)			
	1 year	2 years	3 years	4 years	1 year	2 years	3 years	4 years
I. *Private fixed investment* (64)								
average	0.89	1.42	1.35	1.04	−0.08	0.22	0.54	0.79
median	0.61	1.57	1.36	1.11	−0.04	0.14	0.53	0.79
minimum	−2.45	−5.82	−4.72	−3.32	−1.85	−0.80	−0.71	−0.62
maximum	5.41	4.58	4.04	3.59	0.50	1.06	1.49	2.07
standard deviation	1.44	1.67	1.36	1.11	0.32	0.34	0.41	0.42
II. *Nonresidential structures* (23)								
average	0.19	0.74	1.05	0.98	0.03	0.41	0.81	1.08
median	0.30	0.60	0.76	1.18	0.11	0.44	0.82	1.06
minimum	−2.25	−1.48	−1.25	−1.37	−0.50	−0.11	0.38	0.64
maximum	1.81	3.26	3.80	2.86	0.25	0.67	1.49	2.07
standard deviation	1.00	1.26	1.19	1.03	0.21	0.18	0.23	0.27
III. *Residential structures* (6)								
average	2.20	1.16	0.25	−0.39	0.29	0.76	1.07	1.20
median	3.14	2.28	1.05	0.19	0.34	0.82	1.12	1.21
minimum	−2.45	−5.82	−4.72	−3.32	−0.01	0.36	0.61	0.75
maximum	4.13	3.93	2.27	1.19	0.50	1.06	1.42	1.56
standard deviation	2.32	3.20	2.28	1.44	0.19	0.26	0.28	0.26
IV. *Equipment* (32)								
average	1.22	2.07	1.88	1.42	−0.23	0.00	0.28	0.54
median	0.93	1.87	1.69	1.27	−0.16	0.01	0.28	0.57
minimum	−0.45	−0.51	0.08	−0.27	−1.85	−0.80	−0.71	−0.62
maximum	5.41	4.58	4.04	3.59	0.03	0.68	0.97	1.15
standard deviation	1.24	1.26	1.02	0.86	0.33	0.25	0.32	0.35
V. *Intellectual property* (3)								
average	0.09	0.21	0.29	0.39	−0.09	0.03	0.23	0.43
median	−0.08	0.14	0.34	0.44	−0.13	0.02	0.24	0.43
minimum	−0.40	0.11	0.05	0.03	−0.19	−0.02	0.20	0.40
maximum	0.74	0.37	0.49	0.71	0.05	0.08	0.25	0.47
standard deviation	0.48	0.12	0.18	0.28	0.10	0.04	0.02	0.03

Notes: The table reports statistics on the distribution of PFI price and quantity responses at selected horizons to a (71 basis point) drop in the federal funds rate. Moments are computed across all industries (64 series) along with subgroups comprising nonresidential structures (23 series), residential structures (6 series), equipment (32 series), and intellectual property (3 series).

sixteen quarters. The results are illustrated in Fig. 8.

For nonresidential structures, policy shocks contribute little to fluctuations in real spending. In most cases they account for less than 2 percent of the variance at horizons under two years. These contributions increase over time, but even at a four-year horizon, they seldom exceed 10 percent. Where policy shocks play a larger role is in the volatility of prices. In over half of all industries, they explain 15 to 20 percent of the variance at a four-year horizon.

In the equipment sectors, most of the fallout from policy shocks gets absorbed by quantities rather than prices. The median contribution to the variance in real spending is 6 percent at a two-year forecast horizon. That number jumps to 12 percent at a three-year horizon and to 15 percent over four years. The fraction of overall price volatility that traces to monetary shocks is lower by comparison. For the majority of industries, they account for less than 3

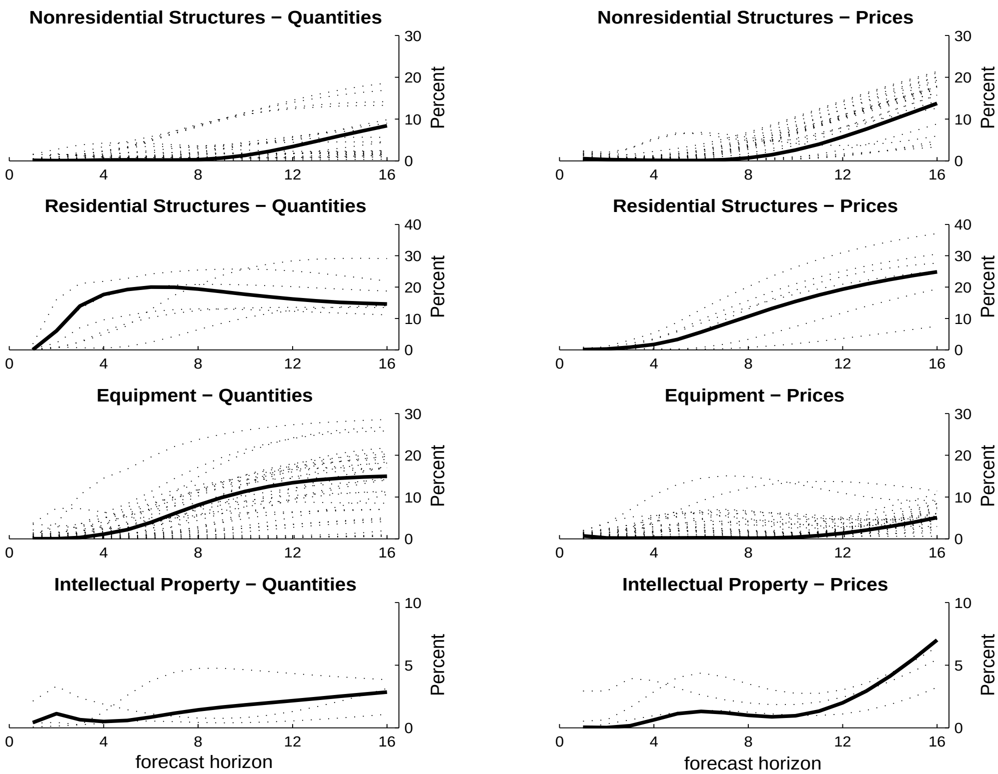

Fig. 8. The contribution that shocks to the federal funds rate make to forecast error variances of PFI quantities (left panel) and prices (right panel) are graphed for horizons up to 4 years. Decompositions are sorted by nonresidential structures, residential structures, equipment, and intellectual property. Solid lines are decompositions for the aggregate quantity and price index.

percent of the variance at horizons of two to three years.

We now turn to residential investment. This industry group is markedly different from nonresidential structures and equipment, where policy shocks mainly affect either the price or quantity margin but not both. After a negative funds rate innovation, both prices and quantities tend to move sharply higher as seen in Fig. 6. Excluding construction of dormitories, residential quantities peak four to six quarters after the shock, and according to Table 1 (third panel), the median response at this horizon is 3.1 percent. The effects are also short-lived. It only takes about three years for average quantities to revert to pre-shock levels. With regard to prices, all but one respond quickly to a monetary shock. The median response is 0.8 percent after two years and exceeds 1.1 percent by the end of year three. At this point, 100 percent of residential prices are statistically different from zero (Fig. 7).

Variance decompositions also underscore the importance of residential investment to the transmission mechanism. Over a one-year horizon, monetary shocks account for 10 percent of the variance in average quantities and nearly 20 percent for single-family structures alone. Two years out, these estimates jump to 16 and 21 percent, respectively. The contributions to price volatility are also significant. Across most industries, 20 to 40 percent of the variance in residential prices is attributable to policy shocks beyond three years.

With only three sectors comprising intellectual property, we are unable to identify any clear pattern in the way market conditions respond to a policy innovation. Sales of entertainment, literary, and artistic originals, for example, grow by 0.8 percent for the first year. Spending of software and research and development, on the other hand, both decline in the months following a funds rate shock. Meanwhile, the corresponding price indexes display significant inertia. Our estimates indicate that two years go by before average prices start rising. Eroding these results even further is the fact that monetary shocks appear to contribute little (less than 5 percent) to the short-run variation in either prices or quantities.

4.4 A Supply and Demand Interpretation

It is natural to interpret industry response functions as the equilibrium result of dynamic interaction between demand and supply curves for capital. According to neoclassical theory, an expansionary monetary shock lifts the demand for fixed investment by lowering the user cost of capital in two ways. One, by cutting the nominal interest rate, monetary policy succeeds in lowering the real interest rate (or required rate of return) on capital.[12] Two, lower interest rates generally increase expected real rates of asset price appreciation (i.e., capital gains). In practice both channels operate simultaneously to boost demand in the short run.[13] Should this lead to increased production of investment goods, as opposed to simply inflating capital prices, depends on the slope or elasticity of the supply curve.

Fig. 9 illustrates this point with a supply-demand diagram. When supply is inelastic, a policy-driven increase in demand bids up the price of capital but has little effect on real quantities (E_1). Alternatively, with an elastic supply curve, demand shocks have a larger impact on quantities but a more limited effect on prices (E_2).[14]

[12]This argument presupposes the existence of nominal frictions, and it also implicitly recognizes the links between the short-term policy rate and long-term rates that influence spending on durable assets.

[13]The user cost of good j (c_j), attributed to Hall and Jorgenson (1967) and discussed in Boivin, Kiley, and Mishkin (2011), can be written as $c_j = p_j \left[((1-\tau)i - \pi^e) - (\pi^e_j - \pi^e) + \delta_j\right]$, where p_j is the relative price of investment in good j, $(1-\tau)i$ is the after-tax nominal interest rate, π^e is expected inflation, $\pi^e_j - \pi^e$ is the expected real rate of appreciation in the price of good j, and δ_j is the asset-specific depreciation rate.

[14]An obvious necessary condition is that demand for fixed investment be responsive to changes in user costs. Estimates of the user cost elasticity are often reported to be both statistically and economically

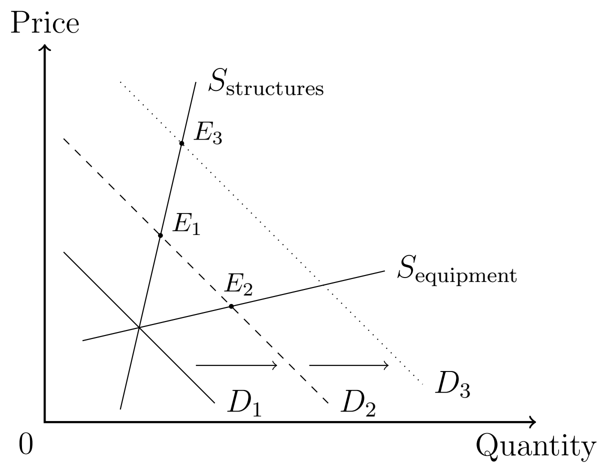

Fig. 9. The diagram illustrates the effects of a positive demand shock on the price and quantity of fixed investment.

We think the situation depicted in Fig. 9 may be important for understanding the dynamics of structures and equipment after a monetary shock. Take the equipment sectors for example. That a negative funds rate innovation tends to increase quantities with little pass-through to prices suggests that equipment supply is relatively elastic. By contrast, evidence on nonresidential structures showing prices rather than quantities adjusting quickly endorses the opposite view that capital supply curves are mostly inelastic in the short run.

To see whether this idea has any merit, we searched for data on industry characteristics that (*i*) should be correlated with the (unobserved) supply elasticity and (*ii*) can be matched to the responses predicted by our VAR. Following Boivin *et al.* (2009), we elected to use gross profit rates from the US Census Bureau, which are available at the sectoral level (by NAICS code) and can be linked to the Underlying Detail Tables for PFI. As an indicator of market power, gross profits should convey information about the slopes of the industry supply curves. Indeed one might expect capital supply to be flatter in competitive industries where profit margins are small but steeper in high-profit industries where firms have greater market power. And if the hypothesis articulated in Fig. 9 is correct, the former would see bigger quantity effects from a policy shock while the latter experiences bigger price effects.

Table 2 reports gross profit rates for the industry groups comprising nonresidential structures, residential structures, and equipment. Data on gross profits for equipment producers come from the Annual Survey of Manufactures (ASM).[15] For residential and nonresidential

significant (e.g., Caballero, 1994; Hubbard, Kayshap, and Whited, 1995; Gilchrist and Himmelberg, 1995; Caballero, Engel, and Haltiwanger, 1995; Cummins, Hassett, and Hubbard, 1996).

[15] In computing gross profits we subtracted production workers annual wages, fringe benefits, and cost of

Table 2
Elasticities and gross profit rates

	Output Elasticity		Price Elasticity		Profit
Nonresidential structures	1.367	$[-0.37, 3.14]$	0.557	$[0.15, 1.00]$	0.429
Residential structures	2.713	$[0.91, 4.52]$	0.300	$[0.07, 0.53]$	0.467
Equipment	2.407	$[0.73, 4.17]$	0.049	$[-0.34, 0.44]$	0.355

Notes: The table reports average output and price elasticities to a 71 basis point drop in the federal funds rate across industries in the nonresidential structures, residential structures, and equipment categories of PFI. The output elasticity is the highest estimate of the quantity response six months to three years after a shock, and the price elasticity is the estimate of the price response during the quarter in which the peak quantity response occurs. Numbers in brackets are 90-percent confidence bands. Profit is the average yearly gross profit rate across industries of a given category and is obtained from the US Census Bureau Business Expenses Survey (structures) or the Annual Survey of Manufactures (equipment).

structures, we use data from the Business Expenses Survey (BES).[16] Table 2 also reports output and price elasticities alongside the profit rates for each group. We define the output elasticity as the maximum point estimate of the quantity response six months to three years after a policy innovation. To fix concepts, the price elasticity is the estimate of the price response in the quarter during which the maximum quantity effect occurs. Values in the table are the (unweighted) mean elasticities across industries.

Survey data reveals that makers of nonresidential structures typically earn higher gross profit rates than equipment producers. We believe this points to greater market power in the former and may well explain the disparate policy effects seen in the table. Estimates of output and price elasticities for nonresidential structures are 1.4 and 0.6 percent, respectively, with only the price effect statistically different from zero. Clearly the opposite is true for equipment, where the output elasticity is 2.4 percent and significant, while the price elasticity is close to zero. Interestingly, these results echo the ones in Hassett and Hubbard (1998) and Whelan (1999). Both studies use a panel of equipment deflators to see whether the effects of an investment tax credit take the form of higher prices or higher quantities. Their regressions consistently return a flat supply curve interpretation, implying that demand stimuli should have significant effects on equipment formation with only modest effects on prices.[17]

We conclude this section with a few remarks on residential structures. Elasticity estimates

materials from the value of shipments and adjusted for changes in finished goods inventories. The ASM contains data at the six-digit NAICS level from 2005 to 2015. We assembled our cross section by averaging the annual profit rates over these eleven years.

[16]Gross profits are the value of finished construction work minus annual payroll minus the cost of subcontracted work. The BES provides data at the six-digit NAICS level for 2007 and 2012 as part of the economic census. We assembled our cross section by averaging the annual profit rates over these two years.

[17]A more detailed analysis of gross profits by industry can be found in the working paper version of this study available on the author's website (http://www.gegivens.weebly.com/).

confirm our earlier findings which show both prices and quantities reacting swiftly to a funds rate innovation. Yet data on gross profits suggest that firms in these industries have substantial market power, indicating that supply curves are fairly inelastic in the short run. At first, this reading of the data may be hard to square with the obvious joint significance of residential prices and quantities. However, we suspect that the reason why both margins are affected here is that the outward shift in demand is large and not solely the result of declining user costs. Fig. 9 illustrates this scenario with an increase in demand from D_1 to D_3, leading to sharply higher prices and quantities (E_3) for residential structures.

One explanation for the demand surge is what Chirinko, Fazzari, and Meyer (1999) describe as the "income effects" deriving from credit constraints. Lower interest rates push down user costs, inducing standard substitution effects that heighten the demand for residential investment. But at the same time, rate cuts increase the borrowing capacity of financially constrained households, creating income effects that put even more upward pressure on demand. As discussed in Iacoviello (2005), the rise in consumer prices after a demand shock reduces the real value of nominal debt obligations. This has a positive effect on net worth, which is linked endogenously to (housing) investment through a binding collateral constraint. Similar balance sheet effects are also relevant for borrowers who seek external finance but face idiosyncratic returns that are unobservable to lenders (e.g., Bernanke, Gertler, and Gilchrist, 1999). In such an environment, positive demand shocks increase borrower net worth and decrease the probability of default. This shrinks the external finance premium, allowing investors to take on more debt and expand their holdings of fixed capital.

5 Sensitivity Analysis

5.1 Shortening the Sample

Concerns about degrees of freedom motivated us to begin our sample in 1959:Q1. Yet studies have shown that many time series relationships exhibit structural breaks around 1980-1982 (e.g., Stock and Watson, 1996). These instabilities are believed to be the result of changes that took place during that time regarding US monetary policy (e.g., Boivin, 2006) and overall business cycle volatility (e.g., Enders and Ma, 2011). Ruling out such instabilities ex ante, which a *fixed*-parameter VAR does by construction, can bias estimates of the response functions (e.g., Pesaran and Timmermann, 2004). To see how vulnerable our results are to this kind of bias, we re-estimate the VARs on a sample that runs from 1981:Q1 to 2007:Q4.[18]

Fig. 10 plots the cross-sectional mean and standard deviation of PFI prices (right column) and quantities (left column) at horizons up to four years. Dashed lines correspond to moments estimated from the shorter sample, and for comparison, solid lines are the benchmark moments. Conditioning estimation on subsample data produces results that are quantitatively different but qualitatively similar to the original estimates. The mean response of PFI quantities, for example, remains hump-shaped, but the peak effect is 90 basis points lower. Regarding investment prices, we see that the mean response across industries is now even more inertial. At a four-year horizon, average prices are just 0.4 percent higher than pre-shock levels. Results also show that the distributional effects identified earlier are still present in subsample data. The standard deviation of PFI quantities rises for the first three quarters but then gradually levels off at around one percent. The standard deviation of prices is actually larger than the full sample estimate one to four years after a policy shock.

5.2 Relaxing the Block-Exogeneity Restrictions

Benchmark results were based on the assumption that aggregate variables are independent from industry prices and quantities. This was implemented by zeroing out the partitions $A_{1,2}(k)$ in (1), thereby making the system exogenous with respect to the macro block. As explained earlier, the goal was to conserve degrees of freedom and to ensure consistent identification of monetary shocks. The drawback of this approach is that it prohibits industry-specific shocks from affecting aggregate dynamics, even in prominent sectors where the data suggests that such feedback may be present. Should this bias estimates of the shocks, inferences about their effects on the cross-sectional distribution of PFI would be incorrect.

In this section we relax the block-exogeneity restrictions by running separate VARs for each industry while leaving $A_{1,2}(k)$ free. Means and standard deviations of the price and quantity responses appear as dotted lines in Fig. 10. Dropping the independence assumption does not change our assessment of the distributional effects of a monetary shock. Compared to the benchmark estimates, the mean response of investment quantities is 9 basis points lower at its peak while the standard deviation is 14 basis points lower. Both are significantly different from zero. On the nominal side, the average price response is inertial even though standard deviations still point to considerable price dispersion three to four years out.

[18]We exclude data from the crisis and recovery years in order to restrict the subsample to the so-called 'Great Moderation' era. Research has shown that both monetary policy and macroeconomic volatility were generally stable during this period (e.g., Stock and Watson, 2003).

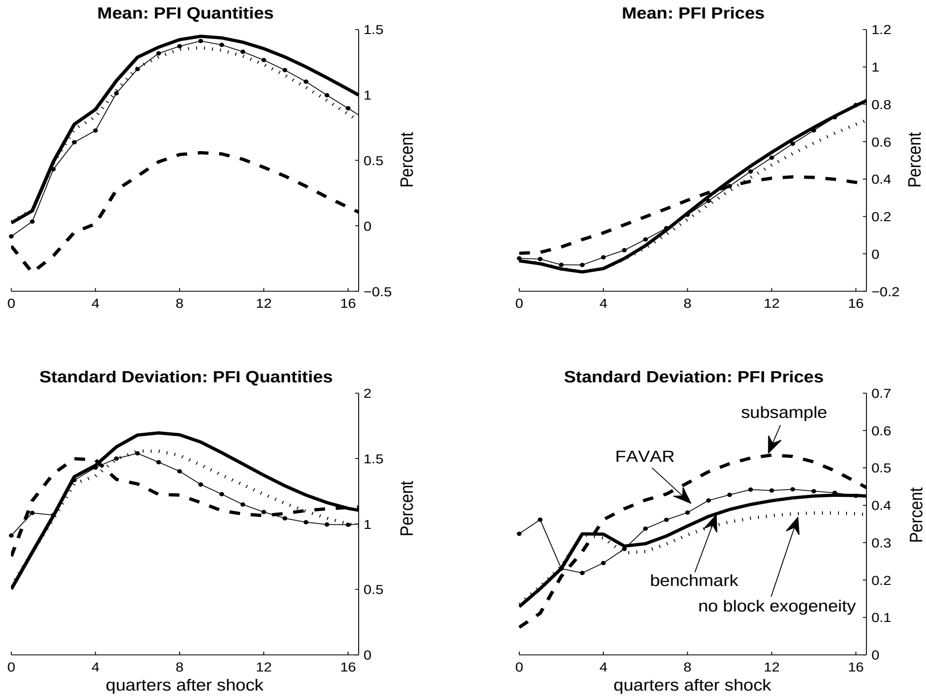

Fig. 10. Left (right) columns show cross-sectional means and standard deviations of PFI quantity (price) responses to a one-standard-deviation drop in the federal funds rate. Solid lines - benchmark estimates; Dashed lines - subsample estimates (1981:Q1-2007:Q4); Dotted lines - estimates that relax block-exogeneity restrictions; Dotted solid lines - FAVAR estimates.

5.3 Relaxing the Block-Diagonal Restrictions

By running separate VARs for each component of PFI, we assume that correlation among industry variables is fully explained through joint dependence on the macro variables. As discussed in section 3, this is equivalent to estimating one large-scale VAR that contains all 64 capital-producing industries but imposes a block-diagonal structure on the partitions $A_{2,2}(k)$ in (1). This assumption greatly reduces the number of free parameters, but it comes at the expense of ruling out any mutual correlation across industries. Ignoring such effects, should they prove important, would raise doubts about our results.

We relax the mutual independence assumption by re-estimating industry responses using the factor-augmented vector autoregression (FAVAR) framework pioneered by Bernanke, Boivin, and Eliasz (2005). In our new model, PFI prices and quantities are driven not by observable macro variables alone, but also by a small set of unobservable factors meant to summarize large amounts of information about the state of capital-goods markets. One could interpret these factors as signaling changes in more loosely-defined economic concepts like "slack," "capacity," or "credit conditions," each capable of affecting outcomes in a multitude of industries simultaneously. This kind of information, while implicit in the large panel of disaggregate PFI data, is not easily captured by one or two observable series.[19]

Let F_t be a $K \times 1$ vector of unobservable factors, with K relatively small, and denote $Y_t' \equiv [\mathrm{GDP}_t\ \mathrm{P}_t\ \mathrm{PFI}_t\ \mathrm{Q}_t\ \mathrm{FUEL}_t\ \mathrm{FFR}_t\ \mathrm{M1}_t]$ the observable macro variables from the upper block of (1). The full inventory of PFI prices and quantities, which we collect in a 128×1 vector X_t, is linked to both sets of factors by a measurement equation

$$X_t = \Lambda^f F_t + \Lambda^y Y_t + e_t, \tag{3}$$

where Λ^f and Λ^y are factor loadings and e_t contains industry-specific shocks that are uncorrelated with F_t and Y_t.[20] The dynamics of (F_t, Y_t) are governed by a transition equation

$$\begin{bmatrix} Y_t \\ F_t \end{bmatrix} = \alpha + \Phi(L) \begin{bmatrix} Y_{t-1} \\ F_{t-1} \end{bmatrix} + \omega_t, \tag{4}$$

where α is a vector of constants, $\Phi(L)$ is a lag polynomial of order four, and $\omega_t \sim$ i.i.d. $(0, \Sigma)$. To identify monetary shocks, we impose on Σ the same orthogonality restrictions used to estimate (2). That F_t is unobservable, however, means (4) cannot be estimated directly. Following Bernanke *et al.* (2005) and Boivin *et al.* (2009), we first recover consistent estimates of the factors $\hat{F}_t$ by extracting the principle components from X_t. We then replace F_t with $\hat{F}_t$ in (4) and estimate responses for $[Y_t'\ \hat{F}_t']'$ using standard methods.[21] From that point it is straightforward to obtain the response of X_t from (3) given estimates of (Λ^f, Λ^y).[22]

For our purposes, the key implication of (3)–(4) is that policy-induced correlation among the variables in X_t will no longer operate exclusively through the macro variables Y_t. Now estimates of the unobserved factors can also exert influence over the common dynamics of X_t, at the same time avoiding the degrees-of-freedom problem that afflicts the benchmark VAR. This is made possible by the fact that $\hat{F}_t$ consolidates into just a few series all of the most relevant information contained in the underlying PFI data.

[19] Latent factor models capable of exploiting information from large data sets have also been used to improve the accuracy of macroeconomic forecasts (e.g., Stock and Watson, 2002) and estimates of the Federal Reserve's policy reaction function (e.g., Bernanke and Boivin, 2003).

[20] Some cross-correlation in e_t is allowed provided it vanish as the number of elements in X_t approaches infinity. See Stock and Watson (2002) for a formal discussion.

[21] Similar to the benchmark VAR, we restrict the partitions $\Phi_{1,2}(L) = 0$ so that monetary shocks can be estimated from the aggregate macro equations alone.

[22] We estimate the factor loadings in (3) by regressing X_t on $\hat{F}_t$ and Y_t. Interested readers should consult Bernanke *et al.* (2005) for more details about this two-step procedure for FAVAR estimation.

The cross-sectional moments implied by the FAVAR model appear as dotted solid lines in Fig. 10. Regarding quantities, we see that the mean response to a policy innovation is close to our benchmark estimate. Apart from a slightly negative impact effect, the average response is hump-shaped, topping out at 1.4 percent nine quarters later. The standard deviation also exhibits the same basic features as before. Again policy shocks generate dispersion in the adjustment of quantities that rises and then stays persistently high for a few years.

Like quantities, the response of investment prices is largely robust to changes in the correlation structure of the model. The mean response is still sluggish, reaching just 0.8 percent after four years. Results also show that the standard deviation of prices is close to the original estimates, particularly after the first year. Their proximity, along with others seen in Fig. 10, suggests that the observable macro factors Y_t may be sufficient to explain much of the policy-induced correlation among the industry components of PFI.

6 Concluding Remarks

We employ disaggregate data on the components of private fixed investment to examine how prices and quantities from each industry respond to an exogenous monetary shock. Scrutinizing the full range of capital-goods producing industries together reveals that while most, but not all, see the volume of real spending go up in the short run, there is considerable heterogeneity in the timing and magnitude of the effects. Moreover, the dispersion in quantities is accompanied by broad cross-sectional variation in the response of investment prices. Thus monetary policy appears to have significant effects on both the composition of fixed-capital formation as well as the distribution of relative investment prices. We interpret this as clear evidence of asymmetry in the monetary transmission mechanism.

In addition to distributional effects, the data exposes certain patterns in the way market conditions within more narrowly-defined asset categories react to a policy disturbance. Across markets for durable equipment, output responses tend to be elastic while price responses tend to be sluggish. Among producers of nonresidential structures, it is prices rather than quantities that are frequently more responsive. Suppliers of residential structures see both margins respond swiftly to a policy shock. These findings along with others documented in the paper contribute to recent efforts that shed light on the transmission mechanism using information drawn from disaggregate data. That we find compelling evidence of heterogeneity in the response functions speaks to the importance of understanding the behavior of capital prices and fixed investment at the industry level.

References

Abel, Andrew B. "Empirical Investment Equations: An Integrative Framework." *Carnegie-Rochester Conference Series on Public Policy*, Spring 1980, 12, pp. 39-91.

Altissimo, Filippo; Mojon, Benoit and Zaffaroni, Paolo. "Can Aggregation Explain the Persistence of Inflation?" *Journal of Monetary Economics*, March 2009, 56(2), pp. 231-41.

Balke, Nathan S. and Wynne, Mark A. "The Relative Price Effects of Monetary Shocks." *Journal of Macroeconomics*, March 2007, 29(1), pp. 19-36.

Barth, Marvin J. III and Ramey, Valerie A. "The Cost Channel of Monetary Transmission." *NBER Macroeconomics Annual 2001*, January 2002, 16, pp. 199-240.

Baumeister, Christiane; Liu, Philip and Mumtaz, Haroon. "Changes in the Effects of Monetary Policy on Disaggregate Price Dynamics." *Journal of Economic Dynamics and Control*, March 2013, 37(3), pp. 543-60.

Bernanke, Ben S. and Blinder, Alan S. "The Federal Funds Rate and the Channels of Monetary Transmission." *The American Economic Review*, September 1992, 82(4), pp. 901-21.

Bernanke, Ben S. and Boivin, Jean. "Monetary Policy in a Data-Rich Environment." *Journal of Monetary Economics*, April 2003, 50(3), pp. 525-46.

Bernanke, Ben S.; Boivin, Jean and Eliasz, Piotr. "Measuring the Effects of Monetary Policy: A Factor-Augmented Vector Autoregressive (FAVAR) Approach." *The Quarterly Journal of Economics*, February 2005, 120(1), pp. 387-422.

Bernanke, Ben S. and Gertler, Mark. "Inside the Black Box: The Credit Channel of Monetary Policy Transmission." *Journal of Economic Perspectives*, Fall 1995, 9(4), pp. 27-48.

Bernanke, Ben S.; Gertler, Mark and Gilchrist, Simon. "The Financial Accelerator in a Quantitative Business Cycle Framework." in John B. Taylor and Michael Woodford, eds., *Handbook of Macroeconomics*, 1(C), North-Holland, Amsterdam, 1999, pp. 1341-93.

Bils, Mark; Klenow, Peter J. and Kryvtsov, Oleksiy. "Sticky Prices and Monetary Policy Shocks." *Quarterly Review*, Federal Reserve Bank of Minneapolis, Winter 2003, 27(1), pp. 2-9.

Blanchard, Olivier J. "Comments and Discussion." *Brookings Papers on Economic Activity*, 1986, No. 1, pp. 153-8.

Boivin, Jean. "Has U.S. Monetary Policy Changed? Evidence from Drifting Coefficients and Real-Time Data." *Journal of Money, Credit and Banking*, August 2006, 38(5), pp. 1149-73.

Boivin, Jean; Giannoni, Marc P. and Mihov, Ilian. "Sticky Prices and Monetary Policy: Evidence from Disaggregated US Data." *The American Economic Review*, March 2009, 99(1), pp. 350-84.

Boivin, Jean; Kiley, Michael T. and Mishkin, Frederic S. "How Has the Monetary Transmission Mechanism Evolved Over Time?" in Benjamin M. Friedman and Michael Woodford, eds., *Handbook of Monetary Economics*, 3(A), Elsevier, Amsterdam, 2011, pp. 369-422.

Caballero, Ricardo J. "Small Sample Bias and Adjustment Costs." *The Review of Economics and Statistics*, February 1994, 76(1), pp. 52-8.

Caballero, Ricardo J.; Engel, Eduardo M. R. A. and Haltiwanger, John C. "Plant-Level Adjustment and Aggregate Investment Dynamics." *Brookings Papers on Economic Activity*, 1995, No. 2, pp. 1-54.

Carlino, Gerald and DeFina, Robert. "The Differential Regional Effects of Monetary Policy." *The Review of Economics and Statistics*, November 1998, 80(4), pp. 572-87.

Chirinko, Robert S.; Fazzari, Steven M. and Meyer, Andrew P. "How Responsive is Business Capital Formation to its User Cost? An Exploration with Micro Data." *Journal of Public Economics*, October 1999, 74(1), pp. 53-80.

Christiano, Lawrence J.; Eichenbaum, Martin and Evans, Charles L. "Monetary Policy Shocks: What Have We Learned and to What End?" in John B. Taylor and Michael Woodford, eds., *Handbook of Macroeconomics*, 1(A), North-Holland, Amsterdam, 1999, pp. 65-148.

Clark, Todd E. "Disaggregate Evidence on the Persistence of Consumer Price Inflation." *Journal of Applied Econometrics*, July/August 2006, 21(5), pp. 563-87.

Cummins, Jason G.; Hassett, Kevin A. and Hubbard, Glenn R. "Tax Reforms and Investment: A Cross-Country Comparison." *Journal of Public Economics*, October 1996, 62(1-2), pp. 237-73.

Davis, Steven J. and Haltiwanger, John H. "Sectoral Job Creation and Destruction Responses to Oil Price Changes." *Journal of Monetary Economics*, December 2001, 48(3), pp. 465-512.

Dedola, Luca and Lippi, Francesco. "The Monetary Transmission Mechanism: Evidence from the Industries of Five OECD Countries." *European Economic Review*, August 2005, 49(6), pp. 1543-69.

Enders, Walter and Ma, Jun. “Sources of the Great Moderation: A Time-Series Analysis of GDP Subsectors.” *Journal of Economic Dynamics and Control*, January 2011, 35(1), pp. 67-79.

Gilchrist, Simon and Himmelberg, Charles P. “Evidence on the Role of Cash Flow for Investment.” *Journal of Monetary Economics*, December 1995, 36(3), pp. 541-72.

Goolsbee, Austan. “Investment Tax Incentives, Prices, and the Supply of Capital Goods.” *The Quarterly Journal of Economics*, February 1998, 113(1), pp. 121-48.

Hall, Robert E. and Jorgenson, Dale W. “Tax Policy and Investment Behavior.” *The American Economic Review*, June 1967, 57(3), pp. 391-414.

Hassett, Kevin A. and Hubbard, Glenn R. “Are Investment Incentives Blunted by Changes in Prices of Capital Goods?” *International Finance*, October 1998, 1(1), pp. 103-25.

Hayashi, Fumio. “Tobin’s Marginal q and Average q: A Neoclassical Interpretation.” *Econometrica*, January 1982, 50(1), pp. 213-24.

Hubbard, Glenn R.; Kashyap, Anil K. and Whited, Toni M. “Internal Finance and Firm Investment.” *Journal of Money, Credit and Banking*, August 1995, 27(3), pp. 683-701.

Iacoviello, Matteo. “House Prices, Borrowing Constraints, and Monetary Policy in the Business Cycle.” *The American Economic Review*, June 2005, 95(3), pp. 739-64.

Jorgenson, Dale W. “Capital Theory and Investment Behavior.” *The American Economic Review*, May 1963, 53(2), pp. 247-59.

Lastrapes, William D. “Estimating and Identifying Vector Autoregressions Under Diagonality and Block Exogeneity Restrictions.” *Economics Letters*, April 2005, 87(1), pp. 75-81.

__________. “Inflation and the Distribution of Relative Prices: The Role of Productivity and Money Supply Shocks.” *Journal of Money, Credit and Banking*, December 2006, 38(8), pp. 2159-98.

Leeper, Eric M.; Sims, Christopher A. and Zha, Tao. “What Does Monetary Policy Do?” *Brookings Papers on Economic Activity*, 1996, No. 2, pp. 1-78.

Loo, Clifton Mark and Lastrapes, William D. “Identifying the Effects of Money Supply Shocks on Industry-Level Output.” *Journal of Macroeconomics*, Summer 1998, 20(3), pp. 431-49.

Pesaran, M. Hashem and Timmermann, Allan. “How Costly is it to Ignore Breaks when Forecasting the Direction of a Time Series?” *International Journal of Forecasting*, July-September 2004, 20(3), pp. 411-25.

Sims, Christopher A. “Interpreting the Macroeconomic Time Series Facts: The Effects of Monetary Policy.” *European Economic Review*, June 1992, 36(5), pp. 975-1000.

Stock, James H. and Watson, Mark W. “Evidence on Structural Instability in Macroeconomic Time Series Relations.” *Journal of Business and Economic Statistics*, January 1996, 14(1), pp. 11-30.

__________. “Macroeconomic Forecasting Using Diffusion Indexes.” *Journal of Business and Economic Statistics*, April 2002, 20(2), pp. 147-62.

__________. “Has the Business Cycle Changed and Why?” *NBER Macroeconomics Annual 2002*, January 2003, 17, pp. 159-218.

Summers, Lawrence H. “Taxation and Corporate Investment: A q-Theory Approach.” *Brookings Papers on Economic Activity*, 1981, No. 1, pp. 67-127.

Tobin, James. “A General Equilibrium Approach to Monetary Theory.” *Journal of Money, Credit and Banking*, February 1969, 1(1), pp. 15-29.

Whelan, Karl. “Tax Incentives, Material Inputs, and the Supply Curve for Capital Equipment.” Federal Reserve Board Finance and Economics Discussion Series, May 1999.

Wu, Jing Cynthia and Xia, Fan Dora. “Measuring the Macroeconomic Impact of Monetary Policy at the Zero Lower Bound.” *Journal of Money, Credit and Banking*, March-April 2016, 48(2-3), pp. 253-91.