Monetary Policy and Investment Dynamics: Evidence from Disaggregate Data

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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 1959-2007. 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.

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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.[1] 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.[2] Among the known determinants of

[1] See Table A in the appendix for a complete list of the separate components of private fixed investment.

[2] 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

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 specific industry or type of capital in question (e.g., Goolsbee, 1998). If true, then such shocks could have nontrivial *distributional* effects as user costs vary and resources get reallocated across sectors. Of course verifying whether policy generates significant 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 patterns or 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

into investment models by Abel (1980), Hayashi (1982), and Summers (1981).

and an integral component of the policy transmission channel central to models of the business cycle. Nevertheless, existing empirical 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. Our estimates would be particularly useful for research on multi-sector models that account for different types of private capital in the production of final goods and services.

To obtain industry-level responses, we employ a structural vector autoregression (VAR) and identify monetary shocks as orthogonalized innovations to the federal funds rate. As shown by Sims (1992) and others, the VAR is a useful framework for estimating the dynamic effects of policy innovations. To preserve degrees of freedom, however, structural VARs typically involve 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 VAR 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.

Results show 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. Thus monetary policy appears to have important 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. Here results indicate that sellers usually raise prices in the short run rather than adjust quantities.

Having documented the industry responses to a monetary shock, we go on to propose a simple demand-and-supply interpretation of the contrast in price and quantity dynamics both *within* and *across* major investment categories. In short, we attribute observed variation in the responses to sectoral differences in the elasticity of capital supply. Support for this idea comes from an analysis of industry-level data on gross profit rates. As a measure of competition, gross profits should correlate with the supply elasticity and so may be useful for explaining how a demand shock gets transmitted into prices versus quantities. When matched to our disaggregate responses, we indeed find that industries whose firms report higher average profits (less competition) tend to be ones in which the price effects are larger and the quantity effects smaller. And the opposite is generally true for low-profit industries, where competition presumably keeps supply conditions more elastic in the short run.

2 Investment Data

Source data on nominal expenditures and price indexes for all categories of private fixed investment (PFI) come from the Underlying Detail Tables for Gross Domestic Product reported by the BEA.[3] The tables disassemble PFI into components, the number of which differ by level of aggregation. There are two components reported at the highest aggregation level, residential and nonresidential investment. The former comprises residential investment in physical structures and durable equipment while the latter consists of nonresidential structures, equipment, and a third group described as intellectual property products.

Fig. 1 illustrates the composition of PFI at the second level of aggregation during the 1970s, 1980s, 1990s, and 2000s. To be clear, what the figure shows is the nominal value of each component expressed *as a percentage* of total PFI averaged over a particular decade. So

[3]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/

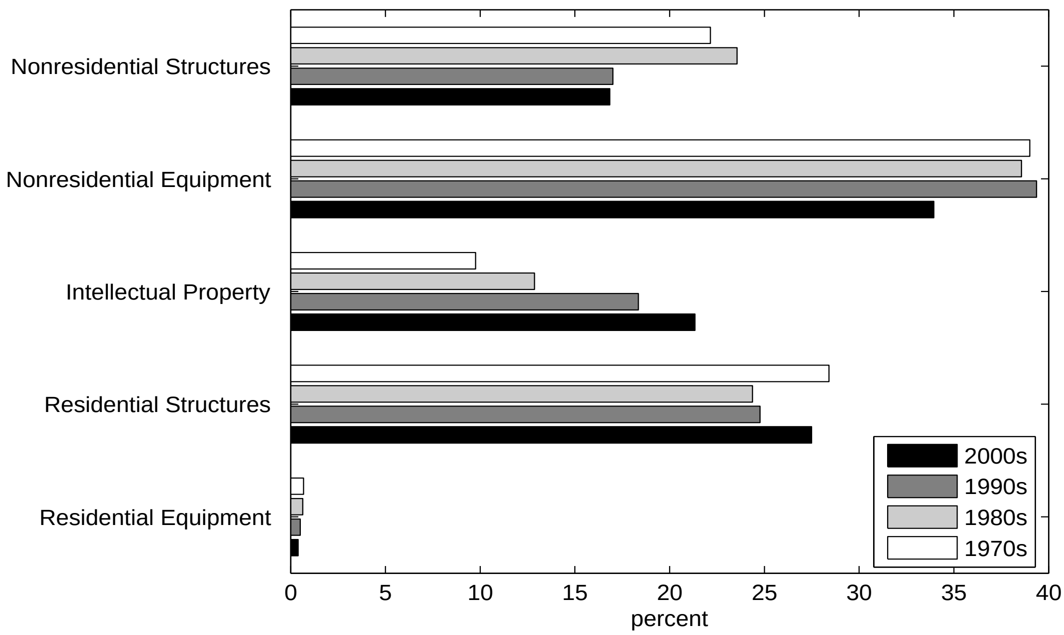

Fig. 1. BEA estimates of average annual nominal spending on nonresidential structures, nonresidential equipment, intellectual property products, residential structures, and residential equipment as a fraction (percent) of total private fixed investment are graphed for 1970-1979, 1980-1989, 1990-1999,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

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. The former grew from 10 to 13 percent of PFI, while the latter shrank from 28 to 24 percent. During the 1990s it was nonresidential structures that witnessed the largest declines. By contrast, investment in intellectual property continued to rise from 13 percent to more than 18 percent over the same period. Through the 2000s intellectual property climbed again to around 21 percent of PFI, while the share of business equipment dropped to 34 percent. The share of residential structures also jumped by 3 percentage points during this decade but was likely driven by the housing bubble that ended abruptly in 2007.

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 in the underlying data, 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. Table A in the appendix lists all of the component series of PFI and reports nominal spending on each one as a share of total private fixed investment in 2007.

The estimation 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 the majority of cases, data are available on a quarterly basis as far back as 1959. A small number of series, however, were excluded because of missing observations. In such instances, the offending series were replaced by data from the next lowest level of aggregation.[4] This left us with a total of 64 disaggregate series on PFI prices and an equal number on nominal investment. The set of variables omitted from our panel represented just 3.4 percent of PFI in 2007.[5]

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 from our use of disaggregate data 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 estimation 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 monetary VAR literature. This block includes seven variables: 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 crude materials to finished goods in the Producer Price Index (PCM), the effective federal funds rate (FFR), and the ratio of nonborrowed to total reserves (NTR).[6] The second block

[4]Separate data on light trucks, including utility vehicles, and other trucks, buses, and truck trailers (lines 56 and 57 of Table A) are not available before 1987. We therefore replace these series with data on trucks, buses, and truck trailers (line 55), which appear without interruption from 1959 on.

[5]The BEA does not compute price indexes for net purchases of used residential or nonresidential structures (lines 34 and 93 of Table A). Both quantities are therefore excluded from the panel.

[6]The relative price of crude materials is included to mitigate the "price puzzle," a temporary deflation following a negative funds rate shock. Sims (1992) points out that such inconsistencies are the result of omitting variables that provide information on expected future inflation. We test this hypothesis in section 5 by comparing our benchmark results to ones obtained from a VAR that excludes PCM as a common factor.

consists of just two variables, one for the disaggregate investment price series of interest and the other for its corresponding real quantity. Separate (9-variable) VARs are then estimated for each of the 64 different capital-producing industries represented in the underlying data.

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 justifiable under 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 $Z_t' = [\mathrm{GDP}_t\ \mathrm{P}_t\ \mathrm{PFI}_t\ \mathrm{Q}_t\ \mathrm{PCM}_t\ \mathrm{FFR}_t\ \mathrm{NTR}_t\ \mathrm{i}_{j,t}\ \mathrm{q}_{j,t}]$, μ is a vector of constants, $A(L)$ is a conformable lag polynomial of finite order, 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 $\mathrm{q}_{j,t}$ 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.

It is worth noting here that forcing $A_{1,2}(k) = 0$ ensures consistent identification of FFR shocks across industries. If instead we left $A_{1,2}(k)$ unrestricted, then the shocks would vary with each new price-quantity pair considered in the VAR. Such a strategy, however, would be at odds with identification of a comprehensive system that incorporates all disaggregate series simultaneously. Nevertheless, in section 5 we relax the block exogeneity 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 the drawback is that policy shocks will not be the same across regressions.[7]

The second set of over-identifying restrictions described by Lastrapes (2006) follows immediately from assuming that industry dynamics are mutually independent after conditioning on the common factors. In other words, the correlation between investment prices and

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

quantities across industries is fully explained by their joint dependence on the macro variables. In practice this is accomplished by including only one ($\mathrm{i}_{j,t}$, $\mathrm{q}_{j,t}$) combination 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 only its own lagged values as well as lags of the common factors. This is equivalent to estimating our 9-variable system separately for each industry while leaving the 2×2 partitions $A_{2,2}(k)$ unrestricted.[8]

We should point out that the block-diagonal restrictions described above are valid insofar as the common factors can account for the sectoral co-movement of investment prices and quantities. Whether our chosen macro variables meet this standard is an open question, and the answer could have consequences for the estimation of industry-level dynamics. 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 among industry groups 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 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. Here 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. 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 $B(L) = (I - A(L)L)^{-1}$.

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. Those

[8]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.

assumptions are that the common factors appearing above FFR_t in (1) respond to policy shocks with a one-quarter delay, whereas variables below the funds rate are permitted to react within the same quarter. Thus by ordering $\mathrm{i}_{j,t}$ and $\mathrm{q}_{j,t}$ last, we are assuming policy can affect industry variables one quarter earlier than the macro variables (excluding NTR).[9]

The data set consists of quarterly observations covering 1959:Q1 to 2007:Q4. The start date was chosen to maximize the sample length and hence degrees of freedom. The end date was chosen to prevent our estimates from being distorted by non-linearities introduced by the effective lower bound on the federal funds rate, which became binding in 2008. Still, one could take issue with our sample period for a couple of reasons. First, a large amount of instability has been documented during this period resulting from shifts in policy behavior and macroeconomic volatility. So in section 5 we see how well our results hold up when estimated on a subsample that displays less instability of this sort. Second, ending the sample in 2007 leaves out potentially informative data from the crisis and recovery period. We therefore re-estimate the model in section 5 using data extended to 2014. To avoid the lower bound issue, we splice the funds rate after 2008:Q3 with observations on the so-called 'shadow policy rate' estimated by Wu and Xia (2016).

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. Finally, four lags are used in estimating (1). We found this number sufficient to stamp out the serial correlation in both macro and industry-level residuals.

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, PCM_t, FFR_t, and NTR_t to a one standard deviation (71 basis point) drop in the federal funds rate. Shaded regions correspond to 90 percent confidence bands.[10]

[9] Should policy affect both macro and industry-level variables with a one-quarter lag, $\mathrm{i}_{j,t}$ and $\mathrm{q}_{j,t}$ would need to be positioned above FFR_t in (1). It turns out that such a re-ordering has little effect on our results since a majority of impact-period responses are not significantly different from zero (see Fig. 5).

[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.

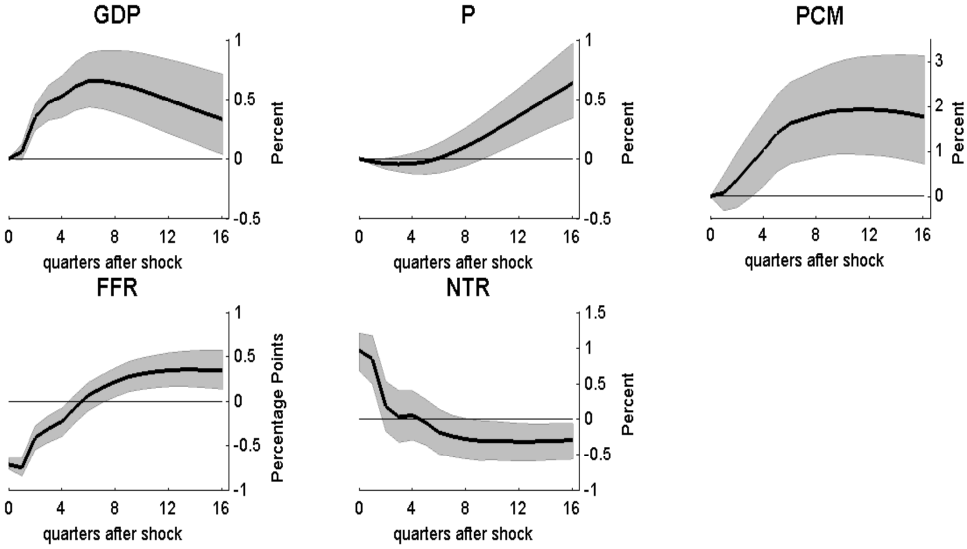

Fig. 2. Impulse responses to a (71 basis point) drop in the federal funds rate are graphed for: **GDP** - real GDP, **P** - GDP chain-type price index, **PCM** - ratio of crude materials to finished goods in the Producer Price Index, **FFR** - effective federal funds rate, and **NTR** - ratio of nonborrowed to total reserves. The shaded regions correspond to 90 percent confidence bands.

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 ratio of nonborrowed to total reserves. It takes over a year for both quantities to return to pre-shock levels. Second, real GDP exhibits the usual hump-shaped pattern seen in numerous studies (e.g., Leeper, Sims, and Zha, 1996). Here we find that it reaches a peak of 0.7 percent six 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 VAR 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. Fourth, a funds rate shock generates a large and sustained increase in the price of crude materials. The maximum impact is nearly 2 percent and occurs at a horizon of three years.

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

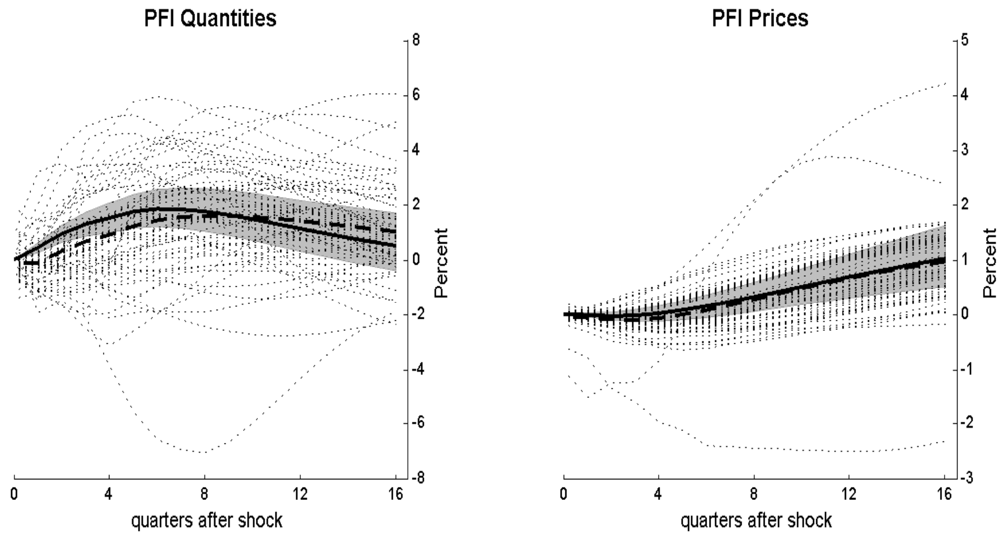

Fig. 3. Impulse responses to a (71 basis point) drop in the federal funds rate are graphed for sectoral PFI quantities (left panel) and prices (right panel). Thick dashed lines are unweighted averages across all sectors. Thick solid lines are the responses of PFI_t and Q_t. The shaded regions are 90 percent confidence bands for the aggregate response functions.

the price level and the quantity of real spending. Together they tell us how market conditions in the industries comprising PFI react to a policy innovation.

Fig. 3 plots the price and quantity responses for each sector. The solid lines are the responses of total private fixed investment, PFI_t, and the 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. The dashed lines are unweighted averages of the price and quantity responses across industries. Their proximity to PFI_t and Q_t suggests that the specific breakdown of investment into its disaggregate components does not have a big impact on aggregate dynamics.

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 (31 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 across industries 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. About half peak between 0 and 2 percent while another third reach highs of 3 to 6 percent. The real effects of monetary policy are therefore 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 a whole year for the average price level to start rising on a consistent basis. Over a period of four years, however, all but two industries experience some inflation, and a majority (two-thirds) sustain anywhere from 0.5 to 1.5 percent.

We should point out here that while expansionary shocks tend to lift investment prices in the long run, a considerable fraction display a small price puzzle in the short run. For example, one year after the shock about 55 percent of all industries witness a decline in prices. These discounts are limited, however, averaging less than 0.3 percent across affected industries. After two years, the share of industries experiencing lower prices drops to 33 percent. That number falls to just 9 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 industry prices and quantities at different horizons (e.g., Baumeister *et al.*, 2013). To that end, Fig. 4 plots smoothed estimates of the probability density functions for the price and quantity responses one year, two years, three years, and four years after the occurrence of a shock.[11] Comparing density estimates 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 is actually highest eight quarters after the shock, at which time over half of all industries have boosted sales by at least 1.5 percent and a few by as much as 5 percent. Beyond that point, the spread of responses begins to narrow. Interestingly, the dynamics of the first and second moments are similar in this case. Notice that the mean quantity response shifts right for the first two years (0.9 to 1.6) 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 after a monetary shock.

Monetary policy clearly has a more permanent 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 0.4 after one year, 0.6 after two years, and 0.8 for years three and four (see Table 1).

Whether price and quantity dispersion is a compelling feature of the data depends to some extent on the significance of our point estimates. To assess significance, we follow Balke and

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

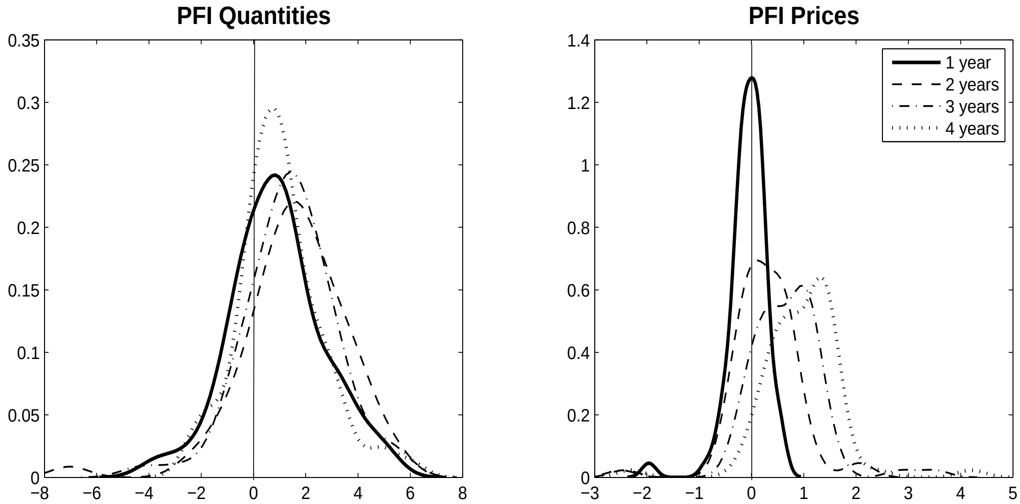

Fig. 4. Smoothed estimates of the density functions for PFI price (right panel) and quantity (left panel) responses to a (71 basis point) drop in the federal funds rate are graphed for 1, 2, 3, and 4-year horizons.

Wynne (2007) by recording the fraction of responses that are statistically different from zero at a 10 percent (p-value) level. A response is significant if at least 90 percent of simulated responses, obtained by sampling from the normal distribution described in footnote 10, are either strictly positive or negative. 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 25 percent. The proportion increases to 60 percent seven quarters after the shock and reverts back to 20 percent by the four-year mark. Regarding PFI prices, barely 14 percent are significant after one quarter, but over 50 percent are significant six quarters later. By the end of the fourth year, as many as 80 percent of industry prices are statistically different from pre-shock levels.

It is possible that the disparate effects of a policy shock reported here are the result of 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 in our data set. 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 private fixed investment, PFI_t, and the deflator, Q_t. As explained in Lastrapes (2006), the simulated series reflects the null hypothesis that the dynamics of aggregate and industry variables 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

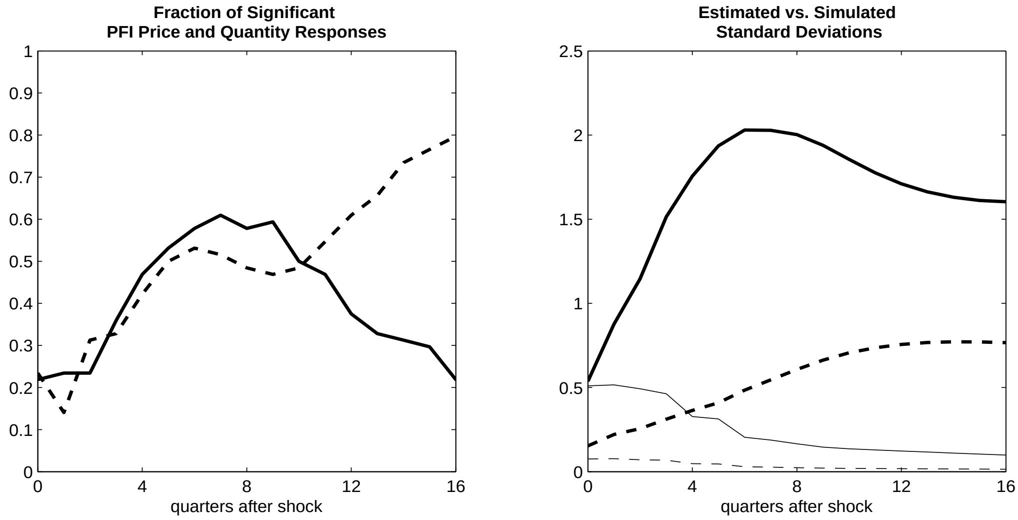

Fig. 5. The left panel shows the fraction of all PFI prices (dashed line) and quantities (solid line) in which the response to a monetary policy shock is significantly different from zero at a 10 percent level. The shock is an unexpected decrease of 71 basis points to the federal funds rate. The right 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.

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 PFI 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 is relatively small and approaches zero a few years after the occurrence of a shock. For example, after four years the standard deviation of the estimated quantity responses is about 150 basis points higher than the mean standard deviation of simulated quantities. The corresponding difference for price dispersion is around 70 basis points. In fact, there is virtually no dispersion in simulated prices after four years. The only horizon at which one might not reject the null is in the impact period and possibly the next quarter. There differences between estimated and simulated standard deviations are much smaller but still positive. Thus it stands to reason that the apparent distributional effects of policy are being driven, not by sampling error or even by a few volatile outliers, but rather by widespread changes in relative investment prices and quantities. We interpret these changes as clear 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 major investment subcategories: nonresidential structures, residential structures, durable equipment, and intellectual property products. Of the 64 PFI components included in our sample, the BEA classifies 23 as nonresidential structures, 6 as residential structures, 32 as equipment, and 3 as intellectual property. Fig. 6 sorts our estimated response functions into these four groups, and Fig. 7 plots the fraction within each group that are significant at a 10 percent level.

Looking only at nonresidential structures, we see substantial heterogeneity in the quantity responses. Table 1 reports descriptive statistics on the distribution of industry responses one, two, three, and four years after the shock. The statistics (second panel) confirm that after one year, roughly half of the 23 industry responses are still negative, with some falling as much as 3 percent. Though most do tend to rise over time, it is clear that the dispersion in quantities persists well beyond one year. As a result, the unweighted mean response is basically zero for the first year and tops out at 0.9 percent by the end of year three. At this point, however, fewer than 25 percent are statistically different from zero as seen in Fig. 7. Thus in the majority of cases, monetary 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. They typically adjust faster and with greater intensity. The median response eight quarters after the shock is 0.6 percent, compared to 0.2 percent when accounting for all of PFI. Moreover, 19 of 23 industry responses (83 percent) are statistically significant at this point. Also note that the standard deviation of prices for nonresidential structures is smaller than the standard deviation for all components of PFI. This implies that the price dispersion observed across all industries is being driven by dispersion elsewhere in the economy–perhaps in the equipment sector–or by discrepancies in the average price dynamics between the four major investment components. Both of these explanations turn out to be consistent with the disaggregate data as shown below.

Behavioral differences between prices and quantities are even more visible in the equipment sector. In these markets, however, it is the real margin that is typically the more elastic. Estimates show that most of the 32 disaggregate quantities peak around eight quarters after

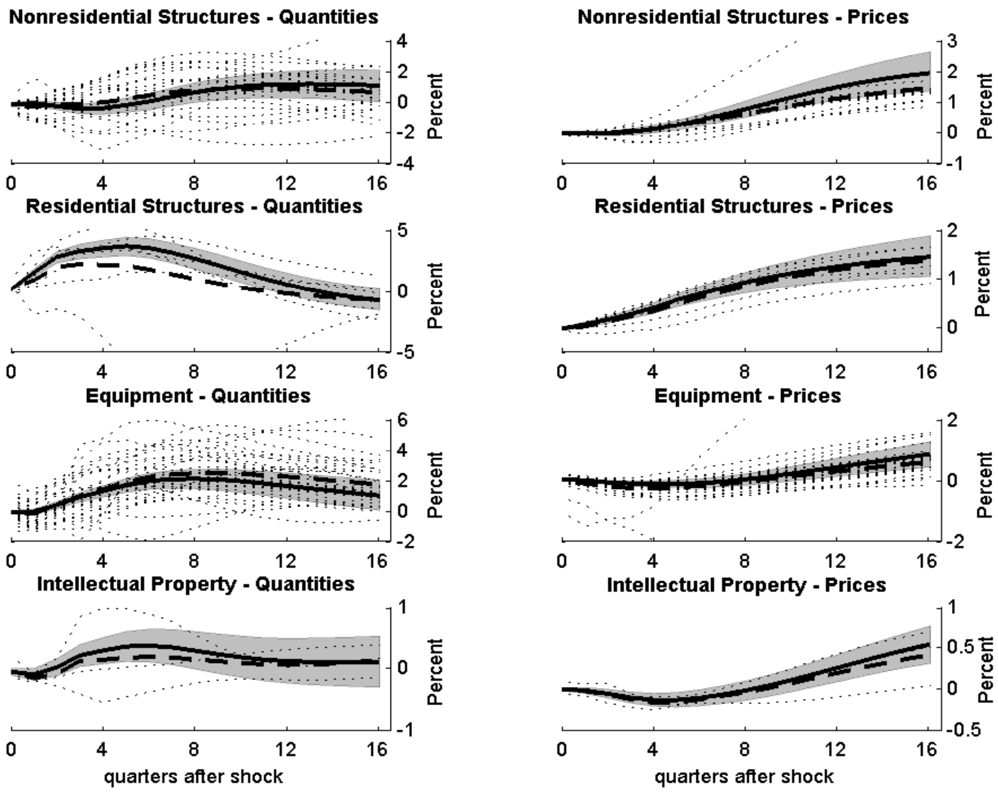

Fig. 6. Impulse responses to a (71 basis point) drop in the federal funds rate for all PFI quantities (left panel) and prices (right panel) are sorted by nonresidential structures, residential structures, durable equipment, and intellectual property products. Thick dashed lines are unweighted averages across all industries within a given category. Thick solid lines are the responses of the aggregate quantity and price index (aggregation level 2 in Table A).

the shock, with 70 percent statistically different from zero according to Fig. 7. As shown in Table 1 (fourth panel), the median response at this horizon is almost three times the median response for nonresidential structures. Also worth noting here is the large cross-sectional variation in the amplitude of responses. In 16 of 32 industries, quantities range from 2.3 to 5.5 percent higher than pre-shock levels.

By contrast, equipment prices are generally slow to adjust. Our findings indicate that two years elapse before average prices respond positively to a drop in the funds rate. Even after three years, fewer than 35 percent of equipment prices are statistically significant. Thus in the short run, expansionary policy can for the most part boost real spending in the equipment sector while keeping average prices subdued. The variation in prices across industries, however, is another matter. Even after excluding computers and peripheral equipment, sectoral price growth after four years spans -0.2 to 2.4 percent.

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	0.90	1.59	1.40	1.02	−0.07	0.28	0.67	0.97
median	0.88	1.55	1.44	0.92	−0.03	0.19	0.65	1.01
minimum	−3.86	−7.03	−4.31	−2.38	−1.96	−2.43	−2.49	−2.30
maximum	5.15	5.46	5.49	6.05	0.53	2.10	3.50	4.20
standard deviation	1.76	2.00	1.71	1.60	0.36	0.61	0.76	0.77
II. *Nonresidential structures* (23)								
average	−0.02	0.76	0.86	0.62	0.12	0.62	1.18	1.45
median	0.03	0.80	1.05	0.49	0.15	0.62	1.03	1.36
minimum	−3.11	−2.45	−2.76	−2.22	−0.33	0.08	0.61	0.85
maximum	1.61	3.18	3.40	5.00	0.51	2.10	3.50	4.20
standard deviation	1.29	1.47	1.41	1.47	0.17	0.36	0.54	0.61
III. *Residential structures* (6)								
average	2.11	0.95	−0.22	−0.75	0.33	0.85	1.18	1.37
median	3.32	2.05	0.24	−0.83	0.40	0.93	1.24	1.45
minimum	−3.86	−7.03	−4.31	−2.38	−0.03	0.41	0.71	0.90
maximum	5.15	4.05	2.39	1.25	0.53	1.12	1.46	1.66
standard deviation	2.94	3.67	2.10	1.26	0.21	0.26	0.28	0.29
IV. *Equipment* (32)								
average	1.40	2.44	2.22	1.71	−0.27	−0.05	0.29	0.60
median	1.28	2.31	1.93	1.23	−0.20	−0.04	0.31	0.61
minimum	−1.32	−1.09	−0.63	−0.60	−1.96	−2.43	−2.49	−2.30
maximum	4.74	5.46	5.49	6.05	0.17	2.03	2.86	2.37
standard deviation	1.46	1.56	1.44	1.43	0.37	0.61	0.75	0.72
V. *Intellectual property* (3)								
average	0.14	0.15	0.06	0.14	−0.16	−0.03	0.20	0.42
median	−0.01	0.13	0.05	0.17	−0.14	−0.01	0.26	0.51
minimum	−0.54	−0.23	−0.18	−0.13	−0.24	−0.17	−0.09	0.05
maximum	0.98	0.54	0.31	0.38	−0.09	0.08	0.43	0.69
standard deviation	0.63	0.32	0.20	0.21	0.06	0.10	0.22	0.27

Notes: The table reports descriptive statistics describing the cross-sectional distribution of PFI price and quantity responses at selected horizons to a one standard deviation (71 basis point) drop in the federal funds rate. Sample moments are computed across the full set of industries comprising private fixed investment (64 series) along with subgroups comprising nonresidential structures (23 series), residential structures (6 series), equipment (32 series), and intellectual property products (3 series).

Whether the contrast in the dynamics of structures and equipment should be viewed as a key feature of the policy transmission mechanism depends to some extent on the role of monetary shocks as a source of industry fluctuations. In what follows we calculate their percentage contribution to the forecast error variances of each PFI price and quantity series. Because our main interest is on business cycle variation, we consider only forecast horizons between one and sixteen quarters. The results are illustrated in Fig. 8.

Regarding nonresidential structures, policy shocks evidently contribute little to short-run fluctuations in real spending. In most industries they account for less than 5 percent of the forecast error variance at horizons under two years. These contributions increase over time, but even at a four-year horizon, they rarely exceed 15 percent. Where policy shocks play a larger role is in the volatility of prices. In over half of the 23 industries, they explain 35 to

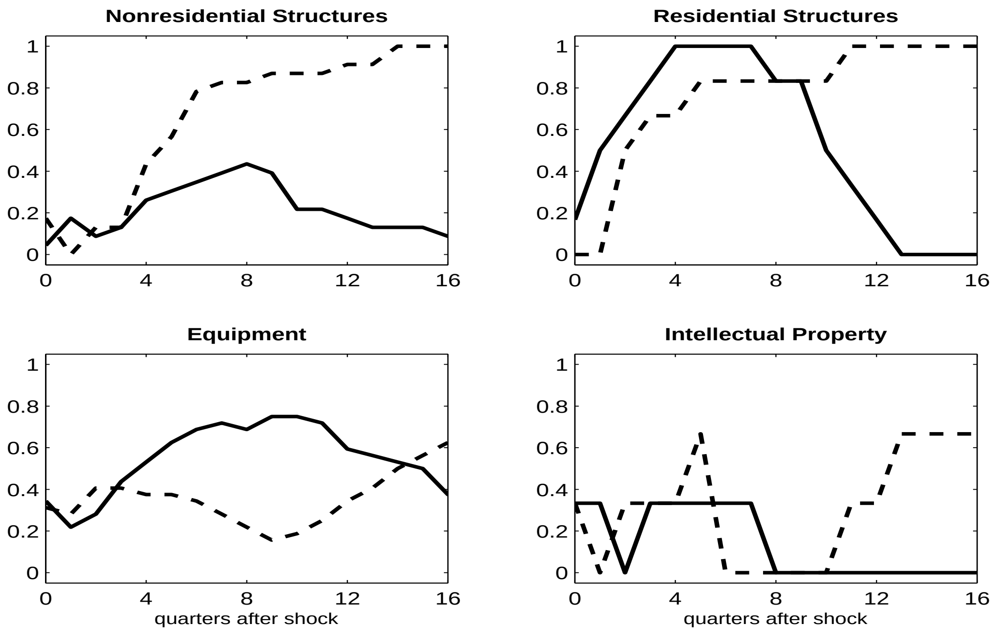

Fig. 7. For each of the four major components of PFI–nonresidential structures, residential structures, durable equipment, and intellectual property products–the fraction of prices (dashed lines) and quantities (solid lines) in which the response to a monetary policy shock is significantly different from zero at a 10 percent level are graphed for horizons of up to four years. The shock is an unexpected decrease of 71 basis points to the federal funds rate.

40 percent of the time-series variance at a forecast horizon of four years.

In the equipment sector most of the fallout from policy shocks gets absorbed by quantities rather than prices. According to estimates, the median contribution to the variance in real spending is 10 percent at a two-year forecast horizon. That number jumps to 17 percent at a three-year horizon and to 21 percent over four years. The fraction of overall price volatility that traces to monetary shocks is much lower by comparison. For the majority of industries, they account for less than 5 percent of the variance at forecast horizons of two to three years.

We now turn to the residential investment category of PFI. The behavior of this sector 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 of residential structures tend to move sharply higher as seen in Fig. 6. For example, output (excluding construction of dormitories) usually peaks four to five quarters after the shock, and according to Table 1 (third panel), the median response at this horizon is 3.3 percent. But the effects are relatively short-lived. It takes on average about three years for quantities to revert to pre-shock levels. With regard to prices, all but one respond quickly to a monetary shock. The median response is 0.4 percent

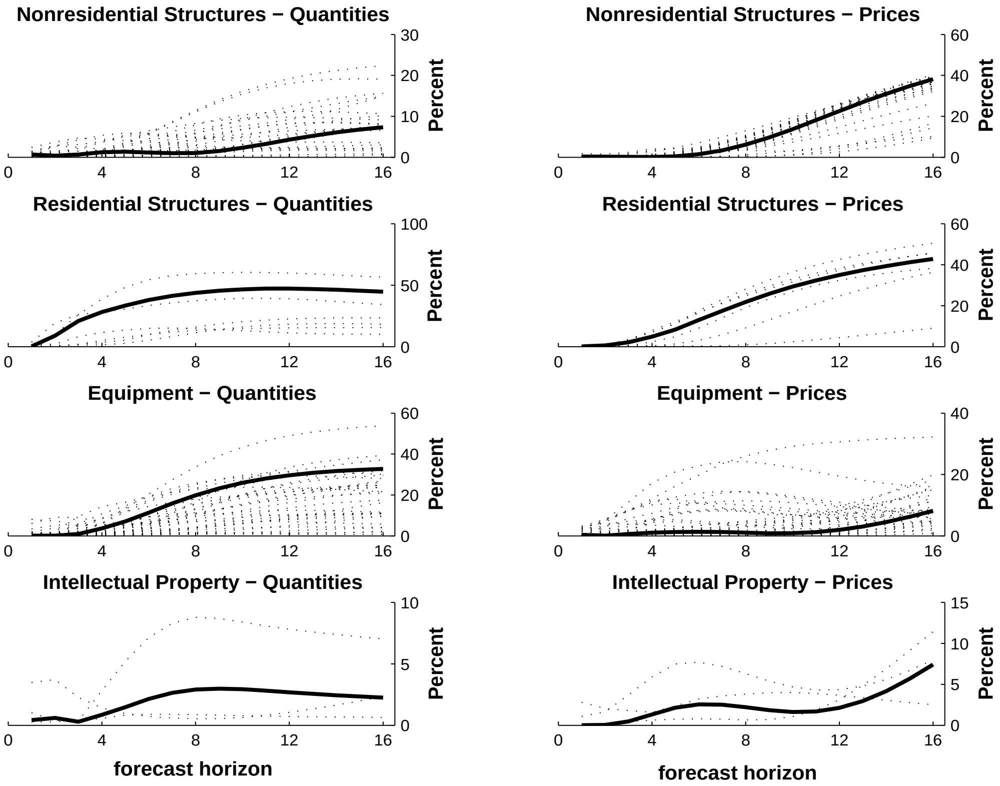

Fig. 8. The contribution that orthogonalized shocks to the federal funds rate make to forecast error variances of PFI quantities (left panel) and prices (right panel) are graphed for forecast horizons of up to 16 quarters. The decompositions are sorted by the four major components of PFI: nonresidential structures, residential structures, durable equipment, and intellectual property products. Thick solid lines correspond to the aggregate quantity and price index (aggregation level 2 in Table A).

after one year and exceeds 0.9 percent by the end of year two. At this point 83 percent of residential prices and quantities are statistically different from zero.

Variance decompositions underscore the importance of residential investment to the transmission mechanism. Over a one-year horizon, monetary shocks account for 15 percent of the time-series variance in average quantities and nearly 40 percent for single-family structures alone. Two years out, the estimates jump to 25 and 50 percent, respectively. The contributions to price volatility are also significant. Across industries, 30 to 40 percent of the variance in residential prices is attributable to policy shocks at horizons beyond three years.

With only three sectors comprising intellectual property products, we are unable to identify any clear pattern in the way market conditions respond to a policy innovation. For example, sales of entertainment, literary, and artistic originals grows by almost one 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, with the former shrinking as much as 0.5 percent. Meanwhile, the price levels observed in these sectors display significant inertia. Response functions indicate that two years go by before average prices start rising.

4.4 A Supply and Demand Interpretation

It is natural to interpret the responses of PFI prices and quantities as the result of interaction between underlying demand and supply curves for capital. According to standard neoclassical theory (e.g., Jorgenson, 1963), an expansionary monetary shock lifts the demand for fixed investment by lowering the user cost of capital in two distinct 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 principle both channels operate simultaneously to boost demand in the short run.[13] But should this lead to increased production of investment goods, as opposed to simply inflating capital prices, depends critically on the slope or elasticity of the supply curve.

Fig. 9 illustrates this point using 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). For such an equilibrium to emerge, it may be that domestic producers have market power or, alternatively, face sharply upward-sloping marginal cost schedules. By contrast, with an elastic supply curve, demand shocks have a larger impact on quantities but a more limited effect on prices (E_2). This outcome would obviously be more consistent with a market structure for capital goods that is open and competitive.[14]

We think the contrast depicted in Fig. 9 is important for understanding the dynamics of structures and equipment after a monetary shock. Take the equipment sector for example. That a funds rate innovation tends to increase real quantities with little pass-through to

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[12] This argument presupposes the existence of price frictions that enable changes in nominal interest rates to affect real interest rates in the short run. It also implicitly recognizes the difference between short-term policy rates and long-term rates that influence spending on durable assets. The transmission mechanism therefore assumes a link between the two through the term structure.

[13] The user cost of good j (c_j), attributed to Hall and Jorgenson (1967) and discussed recently 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 depreciation rate.

[14] An obvious necessary condition here 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 significant (e.g., Caballero, 1994; Hubbard, Kayshap, and Whited, 1995; Gilchrist and Himmelberg, 1995; Caballero, Engel, and Haltiwanger, 1995; Cummins, Hassett, and Hubbard, 1996).

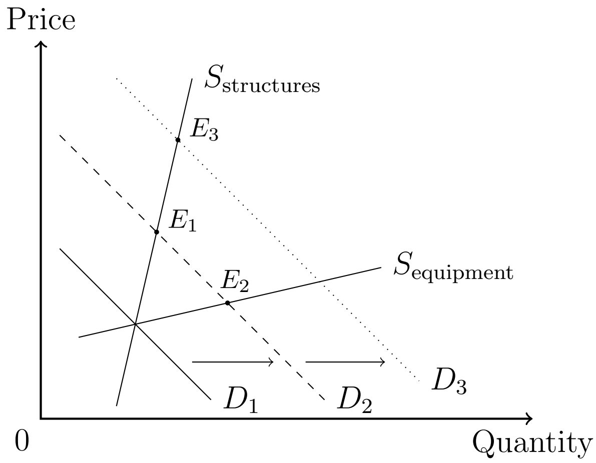

Fig. 9. The supply-demand diagram illustrates the effects of a positive demand shock (e.g., an expansionary monetary policy shock) on the price and quantity of fixed investment in both structures and durable equipment. Differences in equilibrium outcomes, for a given demand shock, are attributed to differences in the relative elasticities of the capital supply curves.

prices suggests that supply is relatively elastic. As it turns out, this echoes results in Hassett and Hubbard (1998), Whelan (1999), and Edgerton (2010), each of whom use a panel of equipment deflators to determine whether the effects of an investment tax credit take the form of higher quantities or higher prices. Their regressions consistently point to a flat supply curve interpretation, implying that tax incentives have significant effects on capital formation with only modest effects on prices. That monetary rather than fiscal stimuli lead to similar outcomes here can be seen more clearly in Table 2, which reports values of the output elasticity for each industry in the equipment category of PFI. We define this variable as the maximum point estimate of the quantity response function six months to three years after a policy innovation. The table also identifies the quarter in which the peak effect occurs.

Results show that 24 of 30 industries exhibit positive and significant output elasticities. Some of the biggest increases occur among producers of heavy equipment (e.g., farm and construction tractors, mining and oilfield machinery, and other construction machinery) and large transportation equipment (e.g., ships and boats, trucks, buses, and truck trailers, and railroad equipment). In these industries production grows anywhere from 3 to 6 percent within three years. Similar gains appear in markets for information processing tools such as computers and peripheral equipment and office and accounting instruments. Although not shown in the table, just five industries register a concurrent price increase that is even significant at a 10 percent level. The rest are either negative or have confidence intervals that

Table 2
Output elasticities for durable equipment

Industry	Elasticity	t	Industry	Elasticity	t
Computers and peripheral equipment	2.867	9	Autos	1.807	5
Communication equipment	1.925	10	Aircraft	*2.728*	12
Electro-medical equipment	2.788	6	Ships & boats	5.291	12
Medical instruments	*0.391*	3	Railroad equipment	3.525	9
Nonmedical instruments	1.647	10	Household furniture	1.657	6
Photocopy & related equipment	*0.882*	6	Other furniture	1.600	6
Office & accounting equipment	4.639	8	Farm tractors	4.614	5
Fabricated metal products	*1.366*	12	Other agricultural machinery	2.840	12
Steam engines	*0.946*	12	Construction tractors	5.932	6
Internal combustion engines	3.303	8	Other construction machinery	4.383	7
Metalworking machinery	1.982	10	Mining & oilfield machinery	5.492	12
Special industry machinery	*0.824*	7	Service industry machinery	1.603	9
General industrial & materials handling	2.181	9	Household appliances	3.432	6
Electrical transmission & distribution	1.600	9	Miscellaneous electrical	3.606	9
Trucks, buses, & truck trailers	4.212	6	Other	2.447	8

Notes: The table reports **output** elasticities to a 71 basis point drop in the federal funds rate for industries in the equipment category of PFI. This elasticity is the highest estimate of the quantity response six months to three years after the shock, and t is the quarter in which the peak effect occurs. Values in italics are not statistically different from zero at a 10 percent level.

contain zero.[15] These findings together favor an elastic supply curve interpretation whereby the effects of a demand shock would show up in quantities more than prices.

While useful for explaining the *average* response of equipment investment, it remains to be seen whether the supply elasticity concept has similar interpretive value concerning the *distribution* of those responses. To explore its role in accounting for the distributional effects of policy, we searched for data on industry characteristics that (*i*) should be correlated with the (market-specific) supply elasticity and (*ii*) could be matched to the responses forecasted by our VAR. Following Boivin *et al.* (2009), we elected to use gross profit rates from the US Census Bureau Annual Survey of Manufactures (ASM), which is available at the sectoral level (by NAICS code) and can be linked to the Underlying Detail Tables published by the BEA.[16] As a measure of market competition, gross profits should convey information about

[15] Higher prices appear mostly in the transportation equipment sector. Lower prices are seen among manufacturers of information processing equipment and may be attributable to difficulties in correcting the deflators for quality improvements. See Goolsbee (1998) and Tevlin and Whelan (2003) for a discussion.

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

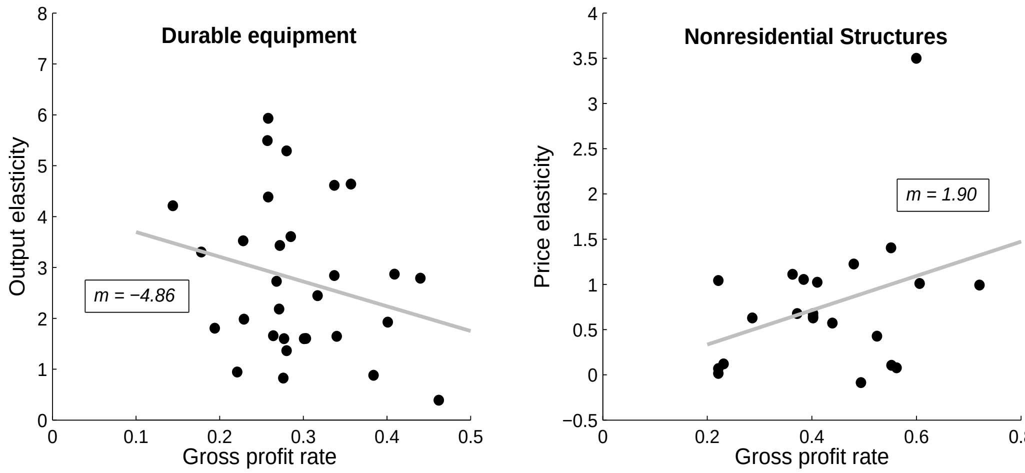

Fig. 10. The left (right) scatter plot shows the link between the output (price) elasticity and gross profit rates by industry for the equipment (nonresidential structures) category of PFI. Solid lines are cross-sectional regression lines with slope m.

the relative slopes of the industry supply curves. Indeed one would expect capital supply to be flatter in more competitive industries where profit margins are smaller on average. And if the basic hypothesis articulated in Fig. 9 is correct, these industries will tend to be the ones that experience the largest quantity effects after a monetary shock.

The left panel of Fig. 10 depicts the relationship between gross profit rates and the output elasticity across equipment-producing industries. It turns out that profits are negatively correlated with quantity responses, implying that more competitive industries (lower profits) usually witness bigger output effects after a funds rate innovation. Examples from this group include internal combustion engines, trucks, buses, and truck trailers, and railroad equipment, where profit margins average just 18, 14, and 23 percent, respectively. The mean profit rate over all industries is 29 percent. Given the slope of the cross-sectional regression line, a jump in profits by 10 percentage points from the mean promises a smaller quantity response by about 0.5 percentage points. This estimate, however, should be interpreted with a degree of caution. Owing to the sample size and variance of output elasticities, the slope coefficient reported in the figure is not statistically significant at regular confidence levels.

Unlike durable equipment, the evidence on nonresidential structures showing prices rather than quantities responding swiftly to a decrease in the funds rate endorses the opposite view that capital supply curves are mostly inelastic in the short run. As a result, in Table 3 we report price elasticities instead of output elasticities for industries in the nonresidential structures category of PFI. To fix concepts, however, we define the price elasticity here as the

Table 3
Price elasticities for nonresidential structures

Industry	Elasticity	t	Industry	Elasticity	t
Office	1.111	12	Communication	1.405	12
Hospitals	*0.016*	2	Petroleum & natural gas	3.499	12
Special care	*0.069*	2	Mining	1.010	12
Medical buildings	1.043	12	Religious	0.630	8
Multimerchandise shopping	0.678	8	Educational & vocational	*0.121*	4
Food & beverage establishments	0.646	8	Lodging	1.054	12
Warehouses	0.572	8	Amusement & recreation	0.677	9
Other commercial	0.629	8	Air	0.427	7
Manufacturing	1.023	12	Land	*0.105*	6
Electric	*-0.085*	3	Farm	0.993	10
Other power	1.226	12	Other	*0.078*	8

Notes: The table reports **price** elasticities to a 71 basis point drop in the federal funds rate for industries in the nonresidential structures category of PFI. This elasticity is the estimate of the price response during the quarter t in which the peak quantity response occurs. Values in italics are not statistically different from zero at a 10 percent level.

value of the price response function during the quarter in which the maximum quantity effect occurs. Our estimates reveal a positive and significant price effect in 16 of 22 industries. We observe some of the highest markups among producers of petroleum and natural gas wells and commercial structures such as offices, medical buildings, and multimerchandise shopping complexes. In the other six industries where price effects are insignificant, the increase in real output after a monetary shock is also not statistically different from zero.[17]

One reason why the supply of nonresidential structures may be inelastic is that firms in these industries have market power. Under such conditions, an outward shift in demand would mainly result in higher prices, with the biggest increases occurring in industries where competition among firms is weakest. To test this hypothesis, we matched industry-level data on gross profit rates to the price responses in Table 3. Again the idea here is that profits should correlate with market power and, by extension, the (in)elasticity of capital supply.

Data on gross profits come from the US Census Bureau Business Expenses Survey (BES). A portion of this survey contains detailed statistics on both the value and cost of specific types of construction work (e.g., office buildings, hospitals, and single-family housing) that

[17]These findings are consistent with the low user cost elasticity for structures estimated by Cummins and Hassett (1992). Chirinko, Fazzari, and Meyer (1999) argue that limited substitution possibilities in production make structures less sensitive to interest rate policies, while Hassett and Hubbard (1997) emphasize the role of adjustment costs stemming from the irreversibility of structures (i.e., lack of efficient resale markets).

Table 4
Elasticities and gross profits for residential structures

Industry	Output Elasticity	Price Elasticity	t	Profit
Singe-family structures	5.272	0.725	5	0.596
Multifamily structures	4.456	0.771	6	0.381
Dormitories	*-1.487*	0.222	2	0.432
Improvements	1.554	0.263	5	0.459

Notes: The table reports **output** and **price** elasticities to a 71 basis point drop in the federal funds rate for industries in the residential structures category of PFI. Values in italics are not statistically different from zero at a 10 percent level. Profit is the average yearly gross profit rate for each industry obtained from the US Census Bureau Business Expenses Survey.

can be matched to the Underlying Detail Tables for PFI.[18] The right panel in Fig. 10 shows the relationship between profit rates and the price elasticity across industries specializing in nonresidential structures. There are two key takeaways from the graph. One, the mean profit rate of 43 percent is considerably higher than that of durable equipment. This result alone points to supply conditions that are on the whole more inelastic. Two, gross profits are positively correlated with the price elasticity. So industries in which firms have greater market power (higher profits) tend to be ones that tolerate the biggest price increases after a monetary shock. Notable examples include petroleum and natural gas wells, power lines and communication towers, and mining construction, where annual profits can run as high as 50 to 60 percent. When viewed together, the full set of cross-sectional results show a 0.2 percentage point increase in the typical price response for every 10 percentage point increase in profits above the mean. To be sure, this estimate does not satisfy the usual criteria for statistical significance due to the limited number of sample observations.

We now turn our attention to the residential structures category of PFI. Table 4 lists output and price elasticities for each industry along with corresponding gross profit rates from the BES. The estimates reinforce our earlier findings which show residential prices and quantities (excluding dormitories) reacting strongly to a funds rate innovation. Meanwhile, data on gross profits suggest that firms in these industries have substantial market power, implying that capital supply curves are fairly inelastic in the short run.

At first glance, this reading of the data is hard to square with the apparent joint significance of our price and quantity responses. Indeed if supply is inelastic, shouldn't the effects of a demand shock be confined to just the prices, as was true for nonresidential structures?

[18] In computing gross profit rates for each sector, we subtracted annual payroll and the cost of subcontracted work from the value of finished construction work. The BES provides data 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.

We suspect 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 equilibrium prices and quantities (E_3) for residential structures.

One possible explanation for the surge in investment demand is what Chirinko *et al.* (1999) describe as the "income effects" originating from credit constraints. Lower interest rates push down the marginal user cost of capital, inducing standard "substitution effects" that heighten the demand for residential investment. But at the same time, rate cuts also enhance the borrowing capacity of financially constrained households and firms, giving rise to "income effects" that put even more upward pressure on demand. As discussed in Iacoviello (2005), for example, the rise in consumer prices following 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 investors 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 aggregate demand shocks both increase entrepreneurial net worth and decrease the expected 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 Extending the Sample

The preceding results are based on data spanning 1959:Q1 to 2007:Q4. The end date was chosen to shield our estimates from potential non-linearities induced by the effective lower bound on the federal funds rate, which became binding amid the financial crisis in December 2008. From this date forward, funds rate observations understated the degree of policy accommodation that was provided at the time through unconventional measures such as large-scale asset purchases and forward guidance. Restricting the sample to the pre-crisis period sidesteps this problem, but it comes at the cost of omitting data that could be useful for discerning the relationship between monetary policy and investment dynamics.

In this section we rerun the estimation using data extended to 2014:Q1. Without meaningful variation in the funds rate post 2008, however, policy innovations cannot be recovered in the usual way. To preserve identification, we splice the funds rate data after 2008:Q3 with observations on the 'shadow policy rate' estimated by Wu and Xia (2016). As explained by the authors, the shadow rate provides an excellent description of the stance of US monetary policy during and in the aftermath of the financial crisis when the actual funds rate was pegged near zero. So throughout this period, policy shocks in our VAR correspond to orthogonalized innovations in the shadow rate rather than the observed funds rate.

Fig. 11 plots the cross-sectional mean and standard deviation of all PFI prices (right column) and quantities (left column) at horizons up to four years. Dashed lines correspond to moments estimated using the extended sample, and for comparison, solid lines are the estimates obtained from the original data set ending in 2007:Q4.[19] Augmenting the data with observations through 2014 does not overturn our basic findings. Average PFI quantities still respond positively to a monetary expansion, with peak effects developing around the two-year mark. Investment prices also remain sluggish for a full year after the emergence of a shock. Qualitative similarities notwithstanding, the mean response of fixed investment does appear to be somewhat weaker in the extended sample. When sorted into investment subcategories, it is clear that what drives this result are smaller average responses of durable equipment and residential structures. Activity in these sectors fell sharply during the recession despite unprecedented levels of monetary stimulus. We speculate that this is diluting the statistical relationship between monetary policy and investment dynamics implied by the full sample.

Though not quite as robust, the distributional effects of monetary policy are still evident in the extended sample. Similar to the benchmark case, the standard deviation of PFI quantities grows for six or seven quarters after the shock before settling down for a time at a level well above one percent. By comparison, it takes about a year longer for the cross-sectional dispersion in PFI prices to reach its highest point.

5.2 Excluding Crude Materials Prices

Recall that PCE–the ratio of crude materials to finished goods in the Producer Price Index–was added to our set of common factors in an effort to ward off the "price puzzle," the conventional (but counterintuitive) finding that an expansionary policy shock leads to a decrease in the price level (e.g., Sims, 1992). The basic idea is that crude materials prices, or something similar like commodity prices, contain information about future inflation. To

[19] In estimating the VAR over the extended sample, we replaced the log ratio of nonborrowed to total reserves (NTR) with the log of the M1 money supply. We did this for two reasons. First, seasonally-adjusted measures of nonborrowed and total reserves (adjusted for regulatory changes in reserve requirements) were discontinued in May 2013. Second, nonborrowed reserves were actually negative from January 2008 through November 2008 because borrowings from Federal Reserve lending facilities during this period were larger than total reserves. Negative nonborrowed reserves renders the log ratio NTR undefined.

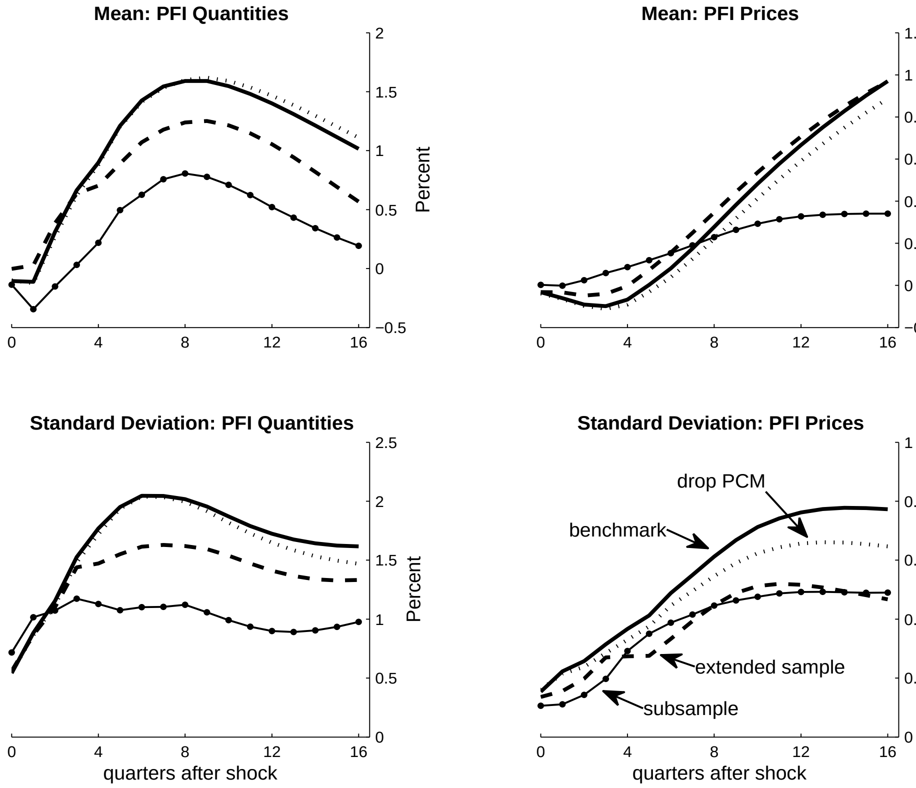

Fig. 11. The left (right) column shows the cross-sectional mean and standard deviation of all PFI quantity (price) responses to an unanticipated unit drop in the policy rate. Solid lines - benchmark estimates; Dashed lines - extended sample estimates (1959:Q1-2014:Q1); Dotted lines - estimates that exclude PCM; Dotted solid lines - subsample estimates (1981:Q1-2007:Q4).

the extent that the Federal Reserve adjusts the funds rate in response to these market-based signals, failure to control for such information in the VAR will contaminate estimates of monetary policy innovations. So part of what the VAR identifies as a funds rate shock may in fact be a systematic policy response to news about the inflation outlook.

In this section we assess whether, or to what length, identification problems responsible for the price puzzle distort estimates of the industry response functions. To that end, we drop PCM from the set of common factors and rerun the VARs on the original sample. The mean and standard deviation of PFI prices and quantities appear as dotted lines in Fig. 11.

Removing crude materials prices from the data set has little impact on the conditional mean and standard deviation of investment quantities, as both measures are nearly indistinguishable from the benchmark estimates at horizons up to two years. The distributional effects on investment prices are also quite small. Compared to the benchmark results, the mean and standard deviation are a bit lower one to four years after a policy shock.[20]

5.3 Shortening the Sample

Concerns about degrees of freedom motivated us to begin our sample as far back as 1959:Q1, the earliest quarter on which disaggregated investment data are available from the NIPA. 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 the early 1980s regarding US monetary policy behavior (e.g., Boivin, 2006) and overall business cycle volatility (e.g., Enders and Ma, 2011). Ignoring information about structural instabilities, which a *fixed*-parameter VAR does by construction, can bias estimates of the response functions (e.g., Pesaran and Timmermann, 2004). To see if our benchmark results are vulnerable to such bias, we estimate the industry VARs using a sample period that runs from 1981:Q1 to 2007:Q4. The mean and standard deviation of all PFI price and quantity responses are depicted as dotted solid lines in Fig. 11.

Conditioning estimation on data that excludes the 1960s and 1970s produces results that are quantitatively different but qualitatively similar to the benchmark findings. The mean response of PFI quantities, for example, remains hump-shaped, but the peak effect is about 75 basis points lower than the full sample counterpart. Regarding investment prices, we see that the mean response across industries is even more inertial for the post-1981 sample. At a four-year horizon, prices are on average just 0.4 percent higher than pre-shock levels. Results also show that the distributional effects identified earlier are still present in subsample data, albeit to a lesser extent. The standard deviation of PFI quantities rises for the first three quarters but then gradually levels off at around one percent. The dispersion in PFI prices is also now uniformly smaller and on par with that seen in the extended sample.

5.4 Relaxing the Block-Exogeneity Restrictions

Our benchmark results were based on the assumption that aggregate macro variables are independent from industry-level prices and quantities. This was implemented by zeroing out the lagged partitions $A_{1,2}(k)$ in (1), thereby making the system exogenous with respect to the macro block. As explained in section 3, the goal here was to conserve degrees of freedom and to ensure consistent identification of monetary shocks across regressions. Of course

[20]The GDP price index is also not greatly affected by the absence of PCM. The response is slighlty smaller (more negative) in the first five quarters but still not significantly different from zero at a 10 percent level.

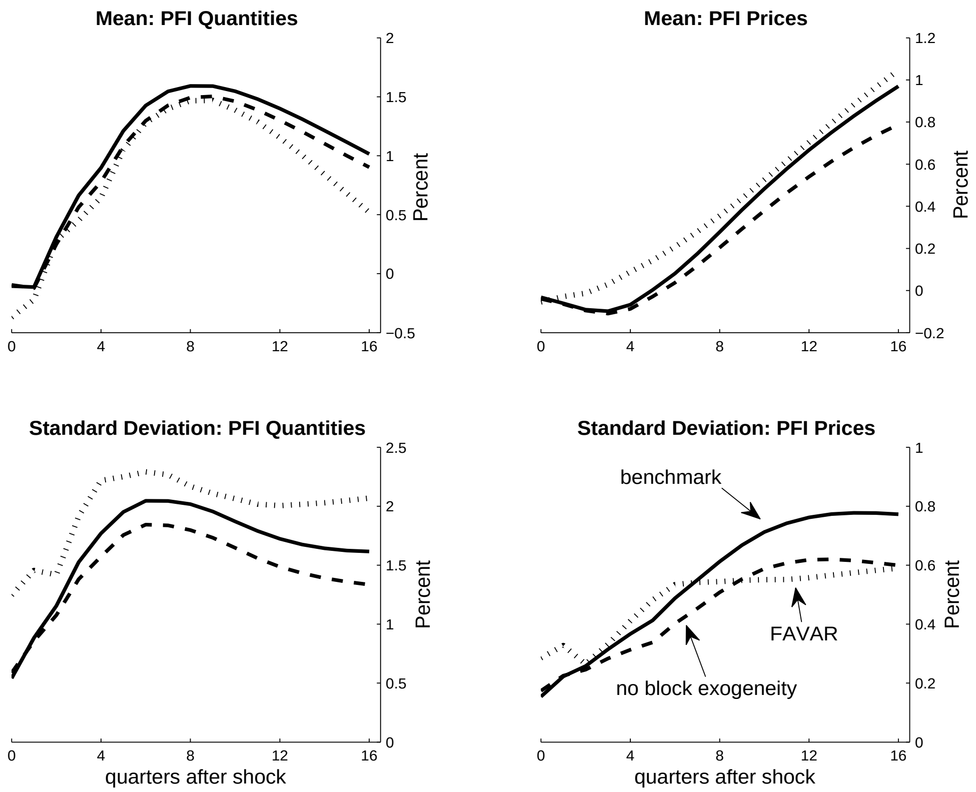

Fig. 12. The left (right) column shows the cross-sectional mean and standard deviation of all PFI quantity (price) responses to an unanticipated unit drop in the policy rate. Solid lines - benchmark estimates; Dashed lines - estimates that relax the block-exogeneity restrictions; Dotted lines - estimates from the FAVAR model.

the drawback of this approach is that it prohibits industry-specific shocks from affecting aggregate dynamics, even in the most prominent sectors where the data suggests that such feedback may be present. Should this bias estimates of monetary 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.[21] The cross-sectional mean and standard deviation of all PFI price and quantity responses appear as dashed lines in Fig. 12. Dropping the independence assumption between macro and industry-level variables does not change our basic assessment of the distributional effects of a monetary shock. At their maximums, the mean response of investment quantities is only 10 basis points lower and the standard

[21]This reduces the degrees of freedom of each macro variable equation by 8, but given the number of sample observations, damage to the accuracy of the coefficient estimates should be limited.

deviation about 20 basis points lower than the benchmark estimates. Both are significantly different from zero. On the nominal side, the average response of PFI prices still exhibits considerable inertia. Estimates of the standard deviation as well point to significant price dispersion three to four years after the occurrence of a shock.

5.5 Relaxing the Block-Diagonal Restrictions

By estimating 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 a single 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). Stated differently, each pair of disaggregate price-quantity equations would have just its own lags along with lags of the macro variables. This assumption significantly reduces the number of free parameters–504 per equation to be exact–but it comes at the expense of ruling out any mutual correlation across sectors. Ignoring such effects, should they prove important, would raise doubts about the validity of our benchmark 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 that in principle 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.[22]

Let F_t be a $K \times 1$ vector of unobservable factors, with K relatively small, and denote $Y_t' \equiv [\mathrm{GDP}_t\ \mathrm{P}_t\ \mathrm{PFI}_t\ \mathrm{Q}_t\ \mathrm{PCM}_t\ \mathrm{FFR}_t\ \mathrm{NTR}_t]$ 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 is a mean zero error term containing industry-

[22]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).

specific shocks that are uncorrelated with F_t and Y_t.[23] 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 impulse responses for $[Y_t' \; \hat{F}_t']'$ using standard methods. From that point it is straightforward to obtain the response of X_t from (3) given estimates of (Λ^f, Λ^y).[24]

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. The gains in efficiency, however, are not without cost. One shortcoming of our FAVAR model, with respect to (1), is the absence of a rich lag structure for individual prices and quantities. Another complication stems from the somewhat arbitrary choice regarding the number of latent factors K. Here we follow Bernanke *et al.* (2005) and Boivin *et al.* (2009) by setting $K = 5$.

The cross-sectional moments implied by (3)–(4) appear as dotted lines in Fig. 12. Regarding PFI quantities, we see that the mean response to a policy innovation is close to our benchmark estimate. Apart from a slightly bigger negative effect in the impact period, the average response profile is hump-shaped, topping out at 1.5 percent nine quarters after the shock. Estimates of the standard deviation also exhibit the same basic features as before. Again monetary shocks generate dispersion in real quantities that first increases and then remains persistently high for several years. If anything, the FAVAR evidence points to even more variation across industries than what is found in the benchmark analysis.

Like quantities, the response of investment prices is generally robust to changes in the

[23]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.

[24]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.

correlation structure of the model. The mean response, for example, is still quite inertial, barely exceeding one percent after four years. During the first few quarters, however, it is somewhat less negative than the benchmark estimate but still not significantly different from zero. Results also show that the standard deviation of PFI prices, particularly in the years right after a shock, is reasonably close to previous VAR-based estimates. Their proximity, along with the others seen in Fig. 12, suggests that the observable macro factors Y_t may be sufficient to explain much of the policy-induced correlation between industry variables.

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.

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Appendix

Table A
Components of private fixed investment in 2007

	Component	Aggregation level 1	2	3	4	5	6
1.	Nonresidential	73.614					
2.	Structures		19.049				
3.	Commercial & health care			6.967			
4.	Office[1]				2.371	2.371	2.371
5.	Health care				1.535		
6.	Hospitals & special care					1.191	
7.	Hospitals						1.058
8.	Special care						0.133
9.	Medical buildings					0.344	0.344
10.	Multimerchandise shopping				1.332	1.332	1.332
11.	Food & beverage establishments				0.308	0.308	0.308
12.	Warehouses				0.648	0.648	0.648
13.	Other commercial[2]				0.773	0.773	0.773
14.	Manufacturing			1.542	1.542	1.542	1.542
15.	Power & communication			3.129			
16.	Power				2.075		
17.	Electric					1.590	1.590
18.	Other power					0.485	0.485
19.	Communication				1.054	1.054	1.054
20.	Mining exploration, shafts, & wells			3.918			
21.	Petroleum & natural gas				3.636	3.636	3.636
22.	Mining				0.282	0.282	0.282
23.	Other structures			3.493			
24.	Religious				0.288	0.288	0.288
25.	Educational & vocational				0.657	0.657	0.657
26.	Lodging				1.304	1.304	1.304
27.	Amusement & recreation				0.469	0.469	0.469
28.	Transportation				0.345		
29.	Air					0.038	0.038
30.	Land[3]					0.307	0.307
31.	Farm				0.241	0.241	0.241
32.	Other[4]				0.170	0.170	0.170
33.	Brokers' commissions on sale of structures				0.130	0.130	0.130
34.	Net purchases of used structures				−0.112	−0.112	−0.112
35.	Equipment		33.948				
36.	Information processing equipment			11.623			
37.	Computers and peripheral equipment				3.362	3.362	3.362
38.	Communication equipment				4.069	4.069	4.069
39.	Medical equipment & instruments				2.772		
40.	Electro-medical equipment					1.396	1.396
41.	Medical instruments					1.376	1.376
42.	Nonmedical instruments				0.999	0.999	0.999
43.	Photocopy & related equipment				0.251	0.251	0.251
44.	Office & accounting equipment				0.169	0.169	0.169

Notes: The table reports nominal spending on each component as a percentage share of total private fixed investment (PFI) in 2007. Shares are listed for every level of aggregation in the underlying NIPA series. The highest aggregation level (*1*) has only two components while the lowest (*6*) breaks PFI into 67 components. At each level, the disaggregate shares sum to 100.

Table A
Continued

	Component	1	2	3	4	5	6
		Aggregation level					
45.	Industrial equipment			7.439			
46.	Fabricated metal products				0.758	0.758	0.758
47.	Engines & turbines				0.437		
48.	Steam engines					0.295	0.295
49.	Internal combustion engines					0.142	0.142
50.	Metalworking machinery				1.091	1.091	1.091
51.	Special industry machinery, n.e.c.[5]				1.346	1.346	1.346
52.	General industrial & materials handling				2.554	2.554	2.554
53.	Electric transmission & distribution apparatus				1.253	1.253	1.253
54.	Transportation equipment			7.237			
55.	Trucks, buses, & truck trailers				3.709		
56.	Light trucks, including utility vehicles[6]					2.531	2.531
57.	Other trucks, buses, & truck trailers[6]					1.178	1.178
58.	Autos[6]				1.866	1.866	1.866
59.	Aircraft				1.085	1.085	1.085
60.	Ships & boats				0.229	0.229	0.229
61.	Railroad equipment				0.349	0.349	0.349
62.	Other equipment			8.116			
63.	Furniture & fixtures				1.614		
64.	Household furniture					0.107	0.107
65.	Other furniture					1.507	1.507
66.	Agricultural machinery				0.888		
67.	Farm tractors					0.373	0.373
68.	Other agricultural machinery					0.515	0.515
69.	Construction machinery				1.380		
70.	Construction tractors					0.108	0.108
71.	Other construction machinery					1.272	1.272
72.	Mining & oilfield machinery				0.693	0.693	0.693
73.	Service industry machinery				1.015	1.015	1.015
74.	Electrical equipment, n.e.c.				0.202		
75.	Household appliances					0.032	0.032
76.	Miscellaneous electrical					0.170	0.170
77.	Other				2.325	2.325	2.325
78.	Less: Sale of equipment scrap, excluding autos			0.467	0.467	0.467	0.467
79.	Intellectual property products		20.617				
80.	Software[7]			9.359	9.359	9.359	9.359
81.	Research & development[8]			8.560	8.560	8.560	8.560
82.	Entertainment, literary, & artistic originals			2.698	2.698	2.698	2.698
83.	Residential	26.386					
84.	Structures		26.007				
85.	Permanent site			13.567			
86.	Single-family structures				11.691	11.691	11.691
87.	Multifamily structures				1.876	1.876	1.876
88.	Other structures			12.440			
89.	Manufactured homes				0.360	0.360	0.360
90.	Dormitories				0.111	0.111	0.111
91.	Improvements				6.577	6.577	6.577
92.	Brokers' commissions & other transfer costs[9]				5.544	5.544	5.544
93.	Net purchases of used structures				−0.153	−0.153	−0.153
94.	Equipment		0.379	0.379	0.379	0.379	0.379

Legend/Footnotes

1. Consists of office buildings, except those constructed at manufacturing sites and those constructed by power utilities for their own use. Includes all financial buildings.

2. Includes buildings and structures used by the retail, wholesale and selected service industries. Consists of auto dealerships, garages, service stations, drug stores, restaurants, mobile structures, and other structures used for commercial purposes. Bus or truck garages are included in transportation.

3. Consists primarily of railroads.

4. Includes water supply, sewage and waste disposal, public safety, highway and street, and conservation and development.

5. n.e.c. Not elsewhere classified.

6. Includes net purchases of used vehicles

7. Excludes software "embedded," or bundled, in computers and other equipment.

8. Research and development investment excludes expenditures for software development. Software development expenditures are included in software investment on line 80.

9. Consists of brokers' commissions on the sale of residential structures and adjoining land, title insurance, state and local documentary stamp taxes, attorney fees, title abstract and escrow fees, and fees for surveys and engineering services.