Heterogeneous Passthrough from TFP to Wages*

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Abstract

What is the impact of firms' productivity shocks on workers' labor earnings? To answer this question, we propose a novel approach to identify firms' productivity shocks that combines a nonparametric production function estimation method with a set of two-way fixed effect regressions to control for differences in labor quality across firms. We apply this method on matched employer-employee data that encompasses the entire population of workers and firms in Denmark between 1995 and 2010. Our dataset allows us to separately study workers that stay in the firm across consecutive periods from those that transition between firms, to control for workers' endogenous job mobility decisions, and to investigate how the passthrough from firms' shocks to wages varies across narrow population groups. We find an elasticity of workers' hourly wages to firms' productivity of 0.08. This implies that a positive shock to firms' productivity of one standard deviation generates an increase of $1,100 US dollars in annual wages for the average worker in Denmark. This result also implies labor supply elasticities of around 5.6. We also find that both persistent and transitory shocks to firms are passed on to wages and that there is marked asymmetry in passthrough between positive and negative productivity shocks. In fact, after controlling for workers' endogenous mobility decisions, the elasticity of hourly wages to a negative productivity shock is twice that of a positive productivity shock of the same magnitude. This suggests that workers are more exposed to negative than to positive shocks to firms' productivity. Furthermore, we find that the changes in wages due to variation in firm productivity are quite persistent and do not dissipate even five years after the shock. By looking at the heterogeneity of passthrough across firm and worker groups, we provide insights about the theoretical mechanisms that could explain the patterns of passthrough we observe in the data.

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1 Introduction

How do fluctuations in firms' idiosyncratic productivity affect workers' wages? How does this vary over time and across firms and workers with different characteristics? The answers to these questions are important for our understanding of how firms differ in their ability to set wages, why workers with similar characteristics receive different salaries across firms, and what is the role of firms' shocks in determining workers' income instability. At the core of these questions is the idea that some of the gains and losses in firms' productivity are passed on to their workers.

In this paper, we use administrative matched employer-employee panel data covering the entire private sector of Denmark to provide new evidence regarding the passthrough of firms' idiosyncratic productivity shocks to workers' wages. Our main object of interest is the elasticity of workers' hourly wages with respect to firms' productivity shocks. We refer to this elasticity as "passthrough".

The richness of our dataset allows us to address two of the main challenges faced by the existing literature. The first challenge is to identify exogenous fluctuations in firm productivity. Most papers in the literature use variations in value added or sales as proxies for shocks to firm productivity. Fluctuations in these variables, however, might not reflect exogenous shocks but rather endogenous decisions by the firm. For example, value-added may increase due to an exogenous increase in productivity, an endogenous increase in the quantity or quality of labor, or both (since the input demand is a function of firm productivity). In this paper, we leverage the rich firm- and worker-level information available in our dataset to estimate total factor productivity (TFP) at the firm level while controlling for the endogeneity of inputs using a dynamic structural model.

To estimate firm TFP, we build on the nonparametric estimation approach proposed by Gandhi, Navarro and Rivers (2018)—hereafter GNR. We deviate from their approach by using individual-level data to control for differences in the quality of labor employed by firms. Specifically, each firm's labor input is calculated as the sum of its workers' observed and unobserved characteristics estimated from a series of two-way fixed effect wage regressions, as in Abowd, Kramarz and Margolis (1999)—hereafter AKM. We deviate from the standard AKM wage model by allowing the firm fixed effects to vary over time, effectively allowing changes in firms' characteristics and productivity to have a dynamic impact on workers' wages. Our estimation approach enables us to identify fluctuations in productivity separately from the fluctuation in inputs, and also enables

us to identify the sign (positive versus negative) and nature (transitory versus persistent) of the shocks. As we shall see, productivity shocks with different characteristics have different impacts on workers' wages.

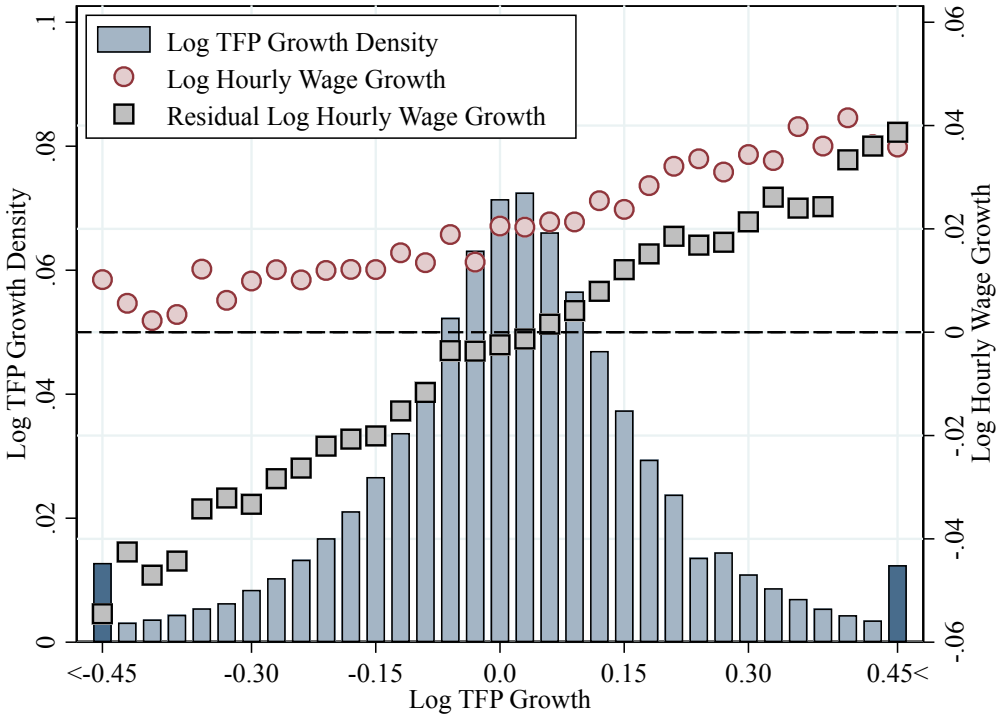
The second challenge is to identify which workers are affected by firms' shocks. In general, the literature has focused on incumbent workers who remain at the firm in consecutive periods ("stayers") since it is straightforward to observe their wages at the firm before and after a shock, and thus estimate the passthrough. This may lead to biased estimates of passthrough if, for example, workers tend to switch jobs rather than experience a large wage decline resulting from a negative firm shock. Since one can only estimate *within-firm* passthrough for workers who choose to remain at their firm, the estimated passthrough for stayers in this example will be biased toward zero. Furthermore, the within-firm passthrough estimates are silent in terms of how firms' shocks affect the wages and employment outcomes of workers who switch between firms.

We address this second challenge in two ways. First, we control for the endogenous separation decision of the worker by exploiting independent variation derived from workers' household linkages. In particular, we predict each worker's probability of staying at a firm as a function of their and their employer's characteristics, as well as their marital status, the observable characteristics of their spouse, and the characteristics of the spouse's employer (if employed). The underlying assumption is that a worker's marital status, their spouse's characteristics, and shocks to their spouse's firm will affect that worker's job mobility decisions, but not the elasticity of wages to productivity in their own firm. Second, we directly study the effect of firm shocks on workers who transition between jobs ("switchers"). Specifically, we measure *between-firm* passthrough by evaluating how wages change for workers who move between employers with different levels and growth rates of productivity. Since these estimates are subject to the same selection problem as the estimates of within-firm passthrough, we employ a similar strategy to correct for selection bias in between-firm passthrough. As we discuss later, correcting for selection turns out to be quite important, especially for the passthrough of negative productivity shocks.[1]

As a preliminary illustration of our main results, Figure 1 shows the relation between firm productivity growth and log hourly wage growth for workers. To construct this figure, we first partition our sample of firms into 41 equally sized bins based on their growth in productivity

[1]The selection bias problem is commonly recognized in the literature. A few papers (e.g., Friedrich, Laun, Meghir and Pisteferri (2019)) have attempted to address the problem using two-step procedures similar to our approach. These papers generally rely on functional form assumptions regarding the stochastic process of firm outcomes and worker earnings to identify the correction terms, rather than using exclusion restrictions on the data.

Figure 1 – Passthrough from Firms' Productivity Growth to Workers' Wages



Note: Figure 1 is based on a pooled sample of firms and workers between the years 1996 to 2010. The blue bars show the share of firms within different bins of the log TFP growth distribution (plotted on the left y-axis). To construct the plot, we separate firms into 41 equally spaced bins between -.45 and 45. The left- and right-most bins, marked in darker blue, encompass the remaining left and right tails of the distribution. The red circles show the average log hourly wage growth for all workers employed by firms within a bin (plotted in the right y-axis). The black squares show the average hourly wage growth after controlling for worker characteristics, firm characteristics, and endogenous selection as explained in Section 3.3 (plotted on the right y-axis).

between periods t and $t-1$, and plot the corresponding density on the left axis. Then, within each bin, we calculate two measures of wage growth for stayers: the average overall change in log hourly wages (plotted as dots on the right axis) and the average *residual* change in log hourly wages after we have controlled for firm and worker observable characteristics and for selection (plotted as squares on the right axis).[2] Two features of this figure are worth noticing. First, the distribution of productivity growth shows significant dispersion, with a substantial share of firms experiencing changes in productivity of more than 30% in a given year.

Second, log hourly wage growth is positively correlated with firm-level productivity growth, especially when firms experience positive growth, but appears to be insulated from the impact of negative productivity changes. In fact, average hourly wage growth is positive across the entire TFP growth distribution (all of the red circles are above zero), suggesting that hourly wages are subject to downward rigidity. Hence, a simple inspection of Figure 1 would indicate that, although there is some passthrough from productivity to wages, it is small and mostly due to positive shocks

[2]Section 3 explains our TFP estimation and selection correction procedures in detail.

to productivity. This conclusion, however, ignores the possibility that the sample of workers who stay in a firm may depend on the magnitude and sign of the productivity shock. When we control for endogenous worker mobility decisions, the picture changes substantially. In particular, we find a significant increase in the slope of the average wage growth line (the black squares), mostly driven by a change over the left tail of the TFP growth distribution. Hence, controlling for selection generates a substantial increase in the elasticity of workers' wages with respect to fluctuations in firm productivity.[3]

Our main empirical analysis consists of a series of worker-level panel regressions that relate log hourly wage growth for stayers (i.e., workers who remain employed in the same firm for at least two consecutive periods) with different measures of firm productivity shocks. Using these regressions, and consistent with the results shown in Figure 1, we find an elasticity of hourly wages to changes in TFP of 0.08, which is economically and statistically significant. Quantitatively, this means that, on average, an individual who works full-time at a firm that experiences a one standard deviation increase in TFP receives an increase in annual earnings of $1,075 US dollars, or around 1.8% of the average annual salary in Denmark. Considering that in a typical year, around 20% of the firms in our sample (which employ around 25% of all private sector workers in Denmark) experience a change in productivity of at least one standard deviation[4] from the mean, we conclude that fluctuations in firm productivity may have important implications for labor earnings inequality and instability.

In the rest of the paper, we study how passthrough varies across different types of firm shocks, different degrees of worker and firm heterogeneity, and across the business cycle. In terms of the types of firm shocks, our empirical approach allows us to study whether shocks with different characteristics have a differential impact on workers' wages. We focus on two important distinctions: positive versus negative shocks, and persistent versus transitory shocks. We find that the elasticity of workers' wages to a negative change in productivity is almost twice as large as the elasticity to

[3]Adjusting for selection affects the passthrough from firm shocks across the entire distribution of hourly wage growth. As we show in Figure A.2 in Appendix (A), not controlling for selection would lead one to conclude that the median worker in firms experiencing a 30% decline in productivity would have experienced no change in their hourly wage, while workers in the 90th percentile would have experienced an increase of 6%. After controlling for selection, we find that the median worker experienced a 2.5% decline in hourly wages, whereas workers in the 90th percentile experienced an increase in hourly wages of 3%. Interestingly, the cross-sectional dispersion of hourly wage growth (measured by the 90th-to-10th percentile differential within each TFP growth bin) is relatively constant across the firm's TFP growth distribution.

[4]The standard deviation of firm TFP growth is equal to 0.23 in our sample.

a positive change in productivity.[5] More precisely, our results indicate that for the average worker, an increase in productivity of one standard deviation generates an increase in annual earnings of $840 US dollars, whereas a decrease in productivity of the same magnitude generates a drop in annual earnings of $1,580 US dollars.

As for the distinction between persistent and transitory shocks, the broad consensus in the literature is that workers' wages respond to persistent changes in firm productivity but do not respond to transitory changes in productivity.[6] Our results are consistent with this evidence in that persistent shocks have higher passthrough than transitory shocks; however, we do find that both types of shocks are statistically and economically significant. Quantitatively, we find that workers in firms experiencing a positive transitory shock of one standard deviation receive an increase in wages of $336 US dollars, whereas a persistent productivity shock of the same magnitude generates an increase in wages of $873 US dollars. Furthermore, by comparing the hourly wage growth at different horizons, we show that persistent shocks to firms' productivity have an almost permanent impact on workers' hourly wages. In contrast, although transitory shocks to productivity have a significant immediate impact on wages, this impact dissipates almost completely three years after the shock.

As we suggested earlier, selection plays an important role in shaping the impact of firms' shocks on workers' wages. Hence, in order to evaluate the extent of the bias generated by selection, we provide a set of results in which we do not control for the endogenous selection of workers. By doing so, we reach two conclusions. First, selection biases the passthrough coefficient toward zero for both positive and negative shocks, reducing the overall impact of the productivity shocks on wages. Second, this bias is much more important for negative than for positive shocks. In fact, if we were to ignore selection, we would conclude that the wage elasticity to positive shocks is almost twice the elasticity to negative shocks, which is the opposite of what we find in our baseline selection-corrected results.

After having characterized the average passthrough from firms' shocks to workers' wages across the population, we discuss several theoretical mechanisms that could rationalize the passthrough patterns we see in the data. In order to test the implications of these different theories, we study

[5] Contract theory provides insights into the transmission of firms' idiosyncratic productivity shocks to workers' wages. For instance, models with firm commitment as in Harris and Holmstrom (1982), would predict that positive shocks are passed to the wages of stayers while negative shocks are not. Models with imperfect monitoring instead (e.g., Lamadon (2016)) predict positive passthrough for both, positive and negative shocks.

[6] See Card, Cardoso, Heining and Kline (2018) and Guiso and Pistaferri (2020) for recent reviews of the literature.

how passthrough varies across different groups of workers and firms. On the worker side, we study how passthrough varies across the workers' income and ability distributions, and for workers of different age and tenure within the firm. On the firm side, we study how passthrough varies across the firms' size, productivity, labor market power, and financial leverage distributions. We conclude by looking at workers who move between firms (switchers).

Overall, we find that passthrough varies considerably across workers and firms with different characteristics. For instance, we find that the passthrough for workers in the top quintile of the income distribution is significantly higher than for workers in the bottom quintile of the income distribution, particularly for persistent negative shocks to productivity. We find similar patterns if we rank workers by their ability, as measured by our AKM estimates. We also find substantial variation in the passthrough across workers of different age and tenure. In particular, we find that relative to younger workers, the hourly wages for older workers increase more after a positive productivity shock and decline less after a negative shock. We also find that the passthrough of negative shocks to workers' wages is hump-shaped in tenure, with recently hired workers (workers with a tenure of less than 2 years) and tenured workers (those with a tenure of 15 years or more) being less exposed to negative shocks than mid-tenure workers.

On the firm side, we find that firms in the top quintile of the TFP distribution have lower passthrough than firms at the bottom quintile of the TFP distribution, as do larger firms and those with higher labor market power (as measured by the employment share of a particular firm within a local labor market).

We also show that the passthrough of persistent productivity shocks is state-dependent, changing substantially over the business cycle. In particular, during an expansion, we find a passthrough elasticity that is in line with our baseline results in that both positive and negative shocks to idiosyncratic firm productivity are significantly passed on to workers' wages. During a recession, however, the passthrough from positive productivity shocks collapses—becoming essentially zero for persistent shocks—whereas the passthrough from negative shocks remains almost unaltered. In other words, instead of recessions being periods in which firms are unable to cut wages when faced with an idiosyncratic negative shock (due to union pressure or concerns about worker effort, for example), we find that during recessions, workers' wages become unresponsive to positive shocks to firms' productivity.

In the last part of the paper, we turn our attention to workers who switch employers. We find

that workers who move from low to high productivity firms experience a significant increase in hourly wages, with larger gains associated with greater moves up the productivity distribution. Quantitatively, workers who experience an increase in hourly log wages of 10 log points move, on average, to a firm with 15 log points higher productivity. A 50 log point wage gain, on the other hand, is associated with a move to a 50 log point more productive firm. Interestingly, these wage gains are not coming from differences in the productivities of the new firms that hire the workers, but rather differences in the productivities of the firms that the workers leave. In fact, workers gaining 50 log points in wages are moving out of firms with 25 log points lower productivity than workers gaining 10 log points in wages, but they are moving into firms with roughly the same productivity. Furthermore, small declines in hourly wages are associated with small *increases* in average firm productivity, whereas large declines in hourly wages are associated with large decreases in average productivity. Notably, independent of the productivity *levels* of the firms over which workers are switching, workers tend to move into firms with higher average productivity *growth*. In fact, the average switcher in every percentile of the wage growth distribution is moving out of a firm with negative productivity growth and into a firm with positive productivity growth.

Finally, we show that our estimates of the passthrough elasticity can be used to recover the implied labor supply elasticity as well. We find an average labor supply elasticity of 5.66, which is consistent with estimates from the recent empirical literature. Through the lens of a simple labor monopsony model, this elasticity implies that firms have substantial labor market power, with wages being set about 15% less than marginal labor productivity on average.

Related Literature. Our paper relates to the rent-sharing literature that studies the relationship between firm shocks and worker earnings. In their seminal contribution, Guiso, Pistaferri and Schivardi (2005) study the passthrough from firms' value-added shocks to wages and the degree of insurance provided by firms using matched employee-employer data from Italy. They find a passthrough coefficient of 0.07 from permanent shocks and almost no passthrough from transitory shocks to firms. Their methodology has been replicated for several countries, including the United States, delivering surprisingly similar results.[7]

We differentiate from Guiso *et al.* (2005), and the subsequent literature, in at least three

[7]Several recent papers study the relation between firm's shocks and worker's wages. See for instance, Friedrich *et al.* (2019), Carlsson *et al.* (2015), Garin *et al.* (2018), Guertzgen (2014), Lamadon *et al.* (2017), Rute Cardoso and Portela (2009), Barth, Bryson, Davis and Freeman (2016), Lamadon (2016), Juhn, McCue, Monti and Pierce (2018) among others. See Manning (2011), Card *et al.* (2018), and Guiso and Pistaferri (2020) for recent surveys.

important ways. First, we measure productivity shocks using a dynamic structural model of firm production. Second, by using hourly wages, we are able to isolate the impact of firm shocks on wages separately from the impact on hours. Third, we control for the endogenous selection of workers in response to firm shocks. Interestingly, we find an average passthrough coefficient that is in line with other estimates in the literature. By separating positive from negative shocks, however, we find substantial asymmetry in the passthrough.

More recently, several authors have used quasi-experiments to identify shocks to firms and how these are passed on workers' wages. For instance, Kline *et al.* (2019) study rent sharing among innovative firms that receive patent approvals. Similarly, Howell and Brown (2019) use cash flows received by firms from government grants as a measure of shocks. These papers focus on a very particular, yet important set of young and small firms, which might not be representative of the entire economy. These quasi-experimental approaches only allows to study positive firm shocks, which we find to have a smaller passthrough than negative shocks. Our methodology, in contrast, allows us to estimate the passthrough for both positive and negative shocks across the entire Danish private sector.

The method we use to estimate firms' productivity is similar to those proposed by Hellerstein and Neumark (2007), Fox and Smeets (2011), and more recently, Bagger, Christensen and Mortensen (2014) and Bagger and Lentz (2019), who also incorporate worker-level characteristics in order to better control for differences in the labor quality across firms. In particular, Bagger *et al.* (2014) also incorporate firm-time fixed effects into an AKM-style wage model, as we do here. We differ from their paper in that our TFP estimation procedure is more flexible and allows the identification of transitory and persistent shocks to firms' productivity. Lochner and Schulz (2020) also merge the AKM approach to measuring labor quality with a production function estimation method similar to what we use in this paper. We differentiate from their study in that we consider a richer set of workers' characteristics in our AKM estimation; more importantly, we allow for the firm effect to vary with time.[8]

The rest of the paper proceeds as follows. In Section 2, we introduce our data sources and discuss our sample selection. Then, in Section 3, we present our estimation strategy. Section 4 discusses the main results of our analysis. We link these results to several possible theories of passthrough in Section 5. Section 6 studies how the passthrough from firms' shocks to workers'

[8]Note that if the firm fixed effect in the AKM wage equation is constant over time, it must be true that there is *zero passthrough* from firm shocks to wages.

wages varies across firms and workers with different characteristics, while Section 7 studies how switching between firms with different productivity levels affects wages. Finally, Section 8 discusses the implications of our estimates for the labor supply elasticity. Section 9 concludes.

2 Data

Our main source of information is a matched employer-employee administrative dataset from Statistics Denmark covering the years 1995 to 2010. We obtain worker-level information from the Integrated Database for Labor Market Research, which is an annual database containing employment and personal/demographic information for the entire population of Denmark. From this dataset, we obtain several key variables such as annual income and hourly wages for each job at which an individual worked during the year, total number of hours and days worked in each job, occupation, labor market status, position within the firm, age, gender, education, and tenure within the firm. Our data also contains an identifier that links workers with their spouse. This information will be crucial when estimating the first stage of the selection model we use in Section 3.3. Our main outcome variable is the log change of average hourly wages. Hourly wages are calculated as the ratio between the annual labor earnings and the total number of hours worked within a year for each worker at each of the firms at which the worker was employed during the year. In this way, we are able to isolate the impact of a shock to firms' productivity on workers' labor earnings from the change in the number of hours worked during the year.

In our baseline sample, we consider workers who are 15 years and older, who are not working in the public sector, or who are not self-employed. We use this sample to estimate the AKM and production models described in Sections 3.1 and 3.2. For our main regression estimates, however, we focus on a subset of full-time workers (defined as individuals who work 30 or more hours per week) whose annualized total labor earnings are above 30,000 Danish kroner (about 4,600 US dollars in 2010). Despite these restrictions, our estimates are based on a large dataset of 8.98 million worker-year observations. Panel A of Table I provides a few basic summary statistics of our worker-level sample for selected years. Our sample of workers (around 0.5 million workers per year) is 30% female, consisting largely of workers with at least some post-secondary education (65% of the sample), and workers between 25 and 55 years old (around 80% of the sample), with an average annual income of $53,103 US dollars in 2010.

We match this individual-level panel to a firm-level panel—the Firm Statistics Register—which

Table I – Summary Statistics

	2000	2005	2010		2000	2005	2010
Panel A: Workers				Panel B: Firms			
Obs. (000s)	469.9	653.3	625.2	Obs. (000s)	29.6	45.2	48.3
% Women	28.0	30.0	31.0				
% High School	33.7	29.6	27.4	Firm Age: % Share of Firms			
				<5	8.9	10.9	11.4
% Age groups				5-10	23.5	44.3	48.5
Below 25	8.69	6.7	8.1	10+	67.6	44.9	40.1
25-35	30.6	26.7	21.4				
36-45	27.0	30.9	31.4	Firm Age: Average Employment			
46-55	23.3	22.3	25.4	<5	6.2	6.3	5.0
Above 55	10.3	13.4	14.0	5-10	35.7	33.9	34.9
				10+	58.2	59.9	60.1
Annual Labor Earnings							
Mean	49,513	53,104	54,176	Firm Size: % Share of Firms			
P10	34,544	35,954	35,954	20	83.0	84.1	87.4
P50	48,533	51,534	52,052	20-100	13.9	13.1	10.4
P90	77,653	83,283	87,553	100-1000	3.0	2.6	2.2
				1000+	0.1	0.1	0.1
Hourly Wages				Firm: Size: % Share of Employment			
Mean	30.35	32.23	32.88	20	24.3	25.5	28.2
P10	20.97	21.82	21.82	20-100	28.1	28.8	26.6
P50	29.46	31.59	31.91	100-1000	36.7	35.2	33.3
P90	47.13	50.55	53.14	1000+	10.8	10.5	11.8

Table I shows different statistics for workers and firms in our baseline sample. All monetary values are converted to US dollars of 2010. To avoid the disclosure of any sensitive information, for all percentiles, we report the mean of all observations *within* a percentile-band rather than individual observations at the percentile cutoff.

contains annual accounting and input use data for the universe of Danish private sector firms.[9] The key firm-level variables we use are annual revenue, value added, capital stock, expenditure intermediate inputs and materials, and employment (in full-time equivalents), as well as firm age, geographic location, and industry. This data allows us to construct robust measures of TFP, following the methods developed by Levinsohn and Petrin (2003), Ackerberg *et al.* (2015), Gandhi *et al.* (2018), and others. We discard firms that are not matched with any individual in our sample of workers. We also discard firms with non-positive or imputed measures of sales, employment,

[9]More precisely, the Firm Statistics Register begins with manufacturing in 1995 and gradually adds other industries, reaching universal coverage of the Danish economy in 2001. Our results do not change if we only consider data starting in 2001.

and other key variables.[10] Panel B of Table I shows a few sample statistics for selected years. Our sample contains around 45,000 firms per year (for a total of 0.6 million across all years), most of which have been in operation for at least 10 years (67.6%). These old, well-established firms represent around 60% of the employment in our sample. As in other countries, the employment size distribution is highly skewed, with a small group of firms with 100 or more employees (3% of firms) accounting for a disproportionate share of the total employment in the Danish economy (45% of employees).

3 Empirical Strategy

In this section, we discuss our empirical strategy to estimate the passthrough from firms' shocks to workers' wages, which consists of three interconnected parts. First, we study a statistical model of earnings that we use to separate the contributions of worker and firm characteristics in determining individual hourly wages (Section 3.1). Second, we discuss our TFP estimation method where we use the results from the statistical model of wages to control for observed and unobserved variation in the quality of the labor inputs employed by the firms (Section 3.2). Third, we discuss how we correct for the selection bias that arises from workers' endogenous mobility decisions. (Section 3.3).

3.1 Two-way Fixed Effect Model of Wages

We start by posing a statistical model of wages that allows us to estimate workers' ability separately from the characteristics and wage-setting policies of the firms where they work. This ability measure will be a crucial input in the TFP estimation method we implement in Section 3.2. More precisely, we consider a modified version of the additive worker-and-firm fixed effect model proposed by AKM in which we assume that the log hourly wage w_{ijt} of an individual i working in firm j in period t is given by

$$w_{ijt} = \underbrace{\alpha_i + X_{it}\Gamma_t}_{\text{Ability Units}} \quad + \quad \underbrace{\psi_{j(i,t)t} + \xi_{ijt}}_{\text{Per-unit Ability Price}} \quad , \tag{1}$$

[10] Our TFP estimation procedure requires data from years $t-1$ and $t-2$ in order to recover productivity in year t. Thus, our final summary statistics and estimation sample consist of firms that are three or more years old.

where α_i is an individual fixed effect, X_{it} is a set of worker observables (including education, occupation, age, experience, tenure and position within the firm), $\psi_{j(i,t)t}$ is a firm-by-time fixed effect that identifies the firm j in which worker i is employed in period t, and ξ_{ijt} is a residual that is uncorrelated to worker or firm characteristics. In this way, we are able to separately identify the component of hourly wages that is due to the fixed and time-varying characteristics of the worker—which we refer to as ability units—from the component of hourly wages that is due to differences across firms and time—which we refer to as the time-varying per-unit ability price paid by the firm. We allow the parameters on individual observable characteristics, Γ_t,to vary by time in order to capture potential changes over time in the individual returns to education, occupation or position within the firm.

Our specification differs from the standard two-way fixed effects regression commonly used in the literature in two crucial aspects. First, most papers use annual labor earnings as their dependent variable, which might confound variations in the wage rate received by a worker and the number of hours worked by an individual during the year. This may be particularly relevant for workers with weak labor market attachment or those who transition between jobs during a year. For this reason, researchers have opted to discard workers with annual labor earnings below a certain minimum threshold.[11] Our dataset contains detailed information on the hours worked and hourly wages for each individual-firm pair during a year, thereby allowing us to use average hourly wages as the main dependent variable.

Second, we do not impose that the contribution of firm characteristics to workers' wages is fixed, as in the standard AKM case, but is rather time-varying, as indicated by the time subscript on $\psi_{j(i,t)t}$. This allows workers to respond to firm-level shocks by moving across firms, which is consistent with the idea that firms' idiosyncratic productivity shocks or other changes in firms' characteristics may impact workers' wages.[12]

As in the standard AKM method, worker and firm-time fixed effects can only be identified within a connected set of firms that are linked through employment transitions.[13] In order to

[11] Typically this minimum threshold is set to a proportion of the total amount of income that a person would earn working at the minimum wage during a fraction of the year (Song *et al.*, 2019).

[12] As we further discuss in Appendix (B), in order to identify the parameters of Equation (1), we require that labor mobility not be correlated with ξ_{ijt}. However, we do allow workers to switch firms in response to shifts in $\psi_{j(i,t)t}$, thereby allowing the passthrough from firm productivity to wages to play a role in worker mobility decisions.

[13] A few other papers allow for time-varying coefficients in AKM regressions. For instance, Bagger *et al.* (2014) allow for occupation-firm fixed and firm-time fixed effects in their wage model and Bagger and Lentz (2019) incorporate time-varying firm-level observables into their estimation. Gregory (2019) analyzes the growth of labor earnings in the context of a two-way fixed effect regression model, implicitly assuming a time-varying firm fixed

estimate the time-by-year fixed effects in Equation (1), we use information on all of the firms in which an individual worked during a given year, along with the corresponding wages and hours. Hence, in our dataset, an individual can appear in different firms within the same year working at different hourly wages. Multiple worker-year observations increase the number of between-firm connections, the number of individual-level observations for each worker, and the size of the connected set.[14]

Since our dependent variable is the log of hourly wages, we are able to include all worker observations—full- and part-time —when estimating Equation (1). This is important for the estimation of firm-level TFP: if we were to restrict our analysis to only full-time workers, or only a worker's primary job, we would be undercounting the labor input for firms that use a higher proportion of part-time workers (which may vary with firm productivity).

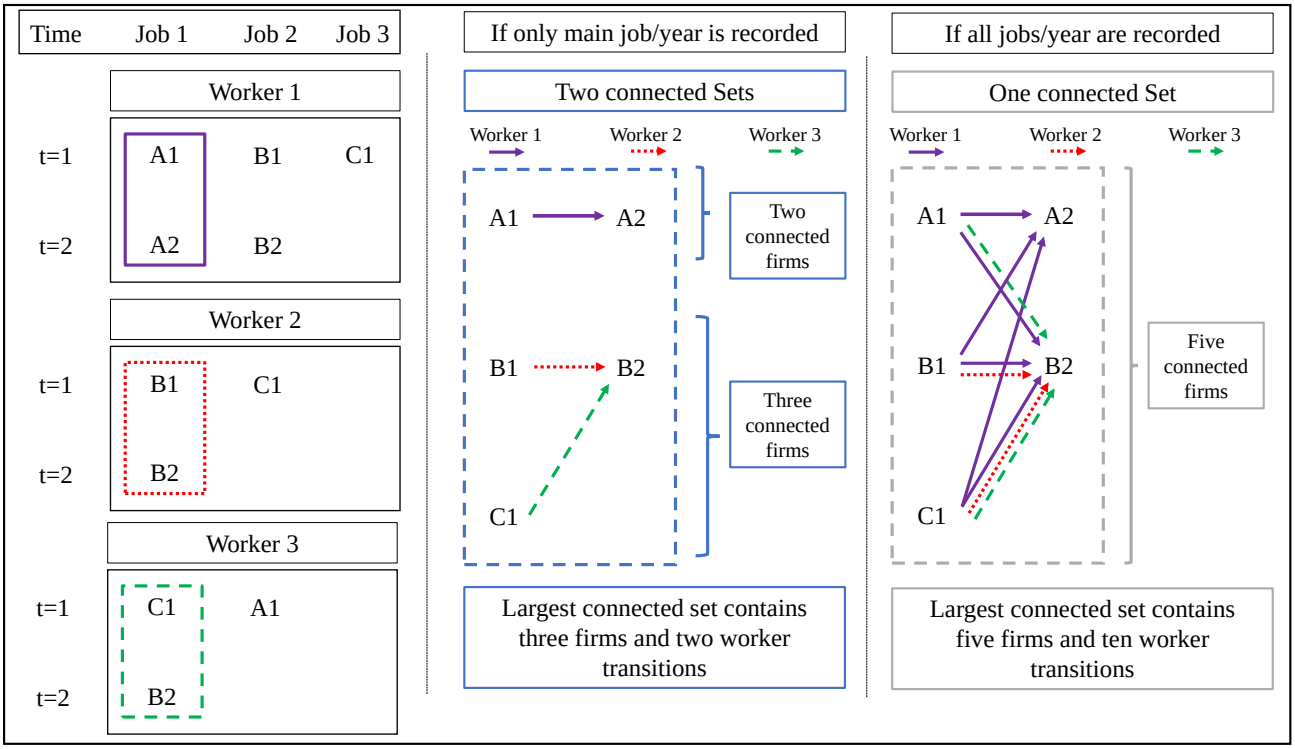
Figure 2 explains how we construct the connected set in our model with firm-time fixed effects and multiple observations per worker within a year. The left panel shows a theoretical set of jobs across two years for three different workers (represented by solid purple, dotted red, and dashed green lines). In this example, worker 1 has three jobs in period 1, working at firms A, B, and C. In period 2, worker 1 has only two jobs—working at firms A and B. Because we estimate firm effects separately for each year, we treat each firm-year observation as a separate firm. Thus, A1 and A2 refer to firm A in periods 1 and 2, respectively. The middle panel shows the network graph of all 5 firm-year nodes if we were to consider only each worker's primary job (as is typically done in the literature). For example, worker 1 moves from A1 in period 1 to A2 in period 2, while worker 3 moves from C1 to B2. The result is two connected sets; the first with firms A1 and A2, and the second (the largest connected set) with firms B1, B2 and C1. Each firm is connected to the rest of their set with just a single worker transition.

The right-most panel of Figure 2 shows the network graph when we consider all of the worker-firm pair information available in a year. In this case, each first-period job worked by an individual is connected to every second-period job worked by that same individual, leading to a connected set including all 5 firms. Moreover, each firm in this larger connected set is connected by at least

effect; Engbom and Moser (2020) is closer to our paper, as they explicitly assume a time-varying fixed effect as we do in Equation (1).

[14]Holding multiple jobs simultaneously in a particular year is quite common among workers in our sample: 54.4% of workers have held a second job at least once while 4.7% of workers have held three or more jobs. In our sample, we consider a worker's top three jobs in a given year (defined by total hours worked that year). It is important to note that, although using multiple firm-year observations per worker improves the accuracy of our estimates, it is not necessary for identification of the model.

Figure 2 – Connected Sets using Multiple Jobs



Note: Figure 2 shows how we identify the parameters of the two-way fixed effect model with firm-year fixed effects and multiple jobs per worker-year. The left panel shows a theoretical set of jobs across two years for three different workers (represented by solid purple, dotted red, and dashed green lines). In this example, worker 1 has three jobs in period 1, working at firms A, B, and C. In period 2, worker 1 has two jobs–working at firms A and B. Worker 2 has two jobs in period 1 (B1 and C1), and only one job in period 2 (B2) whereas worker 3 has two jobs in period 1 (C1 and A1) and only one job in period two (B2). Because we estimate firm effects separately for each year, we treat each firm-year observation as a different firm. Thus A1 and A2 refers to firm A in two different periods. The middle panel shows the network graph of all 5 firm-year nodes if we were to only consider each worker's first job. For example, worker 1 moves from A1 in period 1 to A2 in period 2; worker 2 moves from B1 to B2, and worker 3 moves from C1 to B2. The result is two (disjoint) connected sets, the first with firms A1 and A2, and the second (largest connect set) with firms B1, B2, and C1. Each firm is connected to the rest of the set with just a single worker transition. The right-most panel shows the network graph when we consider all of the available worker jobs information. In this setting, each first-period job worked by an individual is connected to every second-period job worked by that same individual, leading to a connected set including all 5 firms. Each firm in this larger connected set is connected by at least 3 worker transitions to the rest of the set, thereby strengthening the identification of the firm and worker fixed effects.

3 worker transitions to the rest of the set, strengthening the identification of the firm and worker fixed effects.

We estimate the model in Equation (1) using the largest connected set of firm-time observations, constructed as described in Figure 2. Specifically, we pool all of our worker data from 1991 to 2010, providing a robust measure of worker fixed effects and allowing us to compare the levels of firm effects over time without requiring further normalization. In our implementation, the largest connected set includes 94% of the firms and 99% of all of the workers in our original sample.[15] In our regressions, we consider a rich set of worker-level observables including age, occupation, education, position within the firm, labor market experience, and tenure within the firm, most of which are typically absent in other administrative datasets. We further allow for the effect of education,

[15] If we restrict our sample to include only an individual's most important employment connection (by total income), the largest connected set decreases in size, covering only 89% of firms.

occupation, and worker position to change over time in order to capture both the effects of time-varying observable individual characteristics and aggregate trends such as skill-biased technical change and outsourcing.

Using the estimates of our model, we can define an *ability-adjusted log hourly wage,* as

$$\hat{w}_{ijt} = \psi_{j(i,t)t} + \xi_{ijt}, \tag{2}$$

the component of worker i's hourly wage, which is specific to their employment relationship with firm j in year t. We use the change in $\hat{w}_{ijt}$ as our main dependent variable in the regression analysis in Section 4.

Once we have estimated the model in Equation (1), we can decompose the variance of the log hourly wages as follows

$$Var\left(w_{ijt}\right) = \underbrace{Var\left(\alpha_i + X_{it}\Gamma_t\right)}_{\text{Worker Component}} + \underbrace{Var\left(\psi_{j(i,t)t}\right)}_{\text{Firm Component}} + \underbrace{2 \times Cov\left(\alpha_i + X_{it}\Gamma_t, \psi_{j(i,t)t}\right)}_{\text{Wage Sorting Component}} + \underbrace{Var\left(\xi_{ijt}\right)}_{\text{Residual}}, \tag{3}$$

where the first and second components capture the fraction of the variance of the log hourly wages accounted for by heterogeneity across workers and firms, respectively. The third component accounts for the variation in the log hourly wages that can be attributed to the sorting of workers to firms in terms of their wages, that is, how much of the variation in wages is due to the fact that high-ability workers—as measured by $\alpha_i + X_{it}\Gamma_t$—work in high-wage firms—as measured by $\psi_{j(i,t)t}$.

Table II shows the basic statistics from our AKM estimation for two separate periods and for the pooled sample across all years available in our data. We find that around 50% of the variance of the log hourly wages is accounted for by workers' characteristics, and 11% is accounted for by firms' time-varying characteristics. Our estimates also show that sorting accounts for around 1% of the total variation in hourly wages.[16] Our estimates are in line with other studies that also implement the AKM estimator (see for instance, Sorkin (2018), Song *et al.* (2019), and Lamadon *et al.* (2019)). As in these other studies, we find that workers' characteristics accounts for at least

[16]In (Chan, Salgado and Xu, 2019), we use the same estimation method and find strong positive sorting between workers' fixed effects and firm *productivity.* This implies that, although high-ability workers might not seem more likely to work in high-pay firms—as measured by the correlation between the worker fixed effects and firm fixed effects—we find that high quality workers are more likely to work in high-productivity firms—as measured by the correlation between worker fixed effects and firms TPF.

Table II – Variance Decomposition of Log Hourly Wages Using AKM

	1995-2002	2003-2010	Pooled
Worker Heterogeneity	50%	52%	51.0%
Firm Heterogeneity	11%	11.5%	11.3%
Wage Sorting	1.2%	0.9%	1.0%
Wage Sorting Correlation	0.01	0.01	0.02

Note: Table II shows the decomposition of the variance log hourly wages using the AKM estimates, as in Equation (3), for two time intervals and for the pooled sample.

60% of the total dispersion in labor earnings, whereas firms' characteristics account for around 10% of the variation in labor income.

One important concern about our setting—which is common to all AKM fixed effect regressions—is that there may be many firm-time pairs that are weakly connected to the largest connected set. For example, in our dataset, we find that roughly 5.2% of all firm-time observations have only one transition connecting these firms to the largest connected set, with another 13.3% of firm-time observations having only two connections. As noted by Andrews *et al.* (2008), if firm fixed effects are identified using a small number of workers who move across firms, the AKM estimates may be biased, overstating the role of firms relative to the role of sorting in accounting for the variation in labor earnings. Notice, however, that using multiple job observations for workers helps reduce the extent of this limited mobility bias: if we include only one job per worker, we find that 7.0% of firm-time observations have only one link (rather than 5.2% in our baseline sample), and 20.1% have only two links to the largest connected set (versus 13.3% using workers' top three job connections). Furthermore, the limited mobility bias only affects our inference about the importance of firms and sorting in accounting for wage dispersion (the $\psi_{j(i,t)t}$ component), but not the component of the hourly wages accounted for by worker heterogeneity (as measured by $\alpha_i + X_{it}\Gamma_t$), which is crucial for the method we use to estimate firms' TFP.

3.2 TFP Estimation

One of the main challenges in studying the passthrough from firms' shocks to workers' wages is to finding exogenous sources of variation in firms' outcomes. The literature has proposed several measures such as variation in value added (Guiso *et al.*, 2005), export demand shocks (Garin *et al.*, 2018), or cash windfalls from patent allowances or government grants (Kline *et al.* (2019) and Howell and Brown (2019)). In this paper, we instead estimate shocks to firms' TFP using a dynamic structural model of firm production. Our method borrows from the flexible estimation

approach proposed by Gandhi *et al.* (2018). We depart from their approach, however, in that we allow labor inputs to adjust dynamically in response to productivity shocks, and correct for unobserved variation in labor input quality using the estimates from the fixed-effects wage model described in Section 3.1. In order to conserve space, we provide a general overview of our estimation procedure. In a companion paper (Chan *et al.*, 2019), we provide further details of this approach and show how controlling for labor quality impacts the shape and dynamics of the firms' TFP distribution.

There are two challenges we face when identifying a firm's productivity shocks. First, since we are interested in how unanticipated shocks to the firm are passed on to wages—rather than how planned endogenous changes in the input mix affect— we need to identify exogenous changes in firm productivity separately from endogenous shifts in inputs. This is important since wages may be correlated with changes in capital stock or employment as well as changes in productivity. The main difficulty from the fact that firms adjust their capital stock, employment, and other inputs in response to those same exogenous productivity shocks.[17] Second, we need to ensure that our productivity estimation method is consistent with the analysis in the rest of the paper. In particular, we need to recover firms' TFP without relying on the assumption that labor markets are perfectly competitive or that firms are price-takers in labor markets, as both directly preclude the possibility of passthrough from idiosyncratic productivity shocks to wages. We also cannot assume that labor is a "predetermined" input like capital, since our empirical analysis hinges on the observation that labor inputs adjust in response to contemporaneous productivity shocks.

With these considerations in hand, we start by examining a standard representation of a firm-level gross production function in levels:

$$Y_{jt} = F\left(K_{jt}, L_{jt}, M_{jt}\right) \exp\left(\nu_{jt}\right),$$

or in logs,

$$y_{jt} = f\left(k_{jt}, \ell_{jt}, m_{jt}\right) + \nu_{j,t},$$

where ν_{jt} is the Hicks-neutral total factor productivity of firm j in period t. We assume that ν_{jt}

[17] This is the *transmission* bias problem, which has been a central concern of the TFP estimation literature going back to Marschak and Andrews (1944).

is given by

$$\nu_{jt} = \omega_{jt} + \epsilon_{jt},$$

where ω_{jt} is the persistent component of firm productivity, which is assumed to be first-order Markov and is given by $\omega_{jt} = \mathbb{E}[\omega_{jt}|\omega_{jt-1}] + \eta_{jt}$, where η_{jt} is a shock to the *persistent* component of firm's productivity, and where ϵ_{jt} is an i.i.d. ex-post *transitory* shock that is uncorrelated with adjustments in inputs. In what follows, we use the terms *persistent shock* and *transitory shock* to refer to η_{jt} and ϵ_{jt}, respectively. To identify these shocks, we impose standard assumptions on the firms' decisions timing and information sets, which allow us to separately identify η_{jt} and ϵ_{jt}.[18]

As is standard in the literature, we measure Y_{jt} as real revenues, K_{jt} as the real value of the capital stock (using the perpetual inventory method), and M_{jt} with the real value of intermediate input expenditures.[19] Several alternatives have been proposed in the literature to measure the labor input, L_{jt}, demanded by the firm. The most common choices are to use the total number of employees working for firm j in year t or the total number of hours worked by those employees. This measure is not ideal, as cross-sectional differences in the quality or composition of workers across firms will be loaded into ν_{jt}. Similarly, changes in the quality of a particular firm's workforce over time, possibly driven by productivity shocks, will also be interpreted as changes in ν_{jt}. For example, if a firm replaces a full-time janitor with a full-time manager to better organize the cleaning activities of the remaining workers, the firm's output will likely go up, while the number of hours or employees will remain fixed.[20] This introduces significant bias into any estimates of firm productivity.

[18]Following GNR, we assume that capital K_{jt} is a "predetermined" input that is fixed in period $t-1$, and that intermediate materials M_{jt} are a flexible input chosen every period. We depart from their framework in allowing labor L_{jt} to be a dynamic input, while GNR assumes that labor is predetermined like capital. The timing of the model is such that firms enter period t knowing K_{jt}, L_{jt-1}, and, ω_{jt-1}. They then observe $\eta_{j,t}$ and choose L_{jt} (which is allowed to depend arbitrarily on L_{jt-1} through adjustment costs or other factors) and M_{jt} (which does not depend on M_{jt-1}). After the input decisions are set, the firm observes ϵ_{jt}. We assume that firms can adjust wages in response to both shocks, but that firms are price-takers in output markets and the market for intermediate materials.

[19]Using revenues as our measure of output implies that our measure of TFP is "revenue" TFP rather than "quantity" TFP and thus contains both variation in production efficiency, as well as potential variation in output demand. We do not see this as a problem in our context, as we are agnostic about the source of the firm shock, as long as it is exogenous to the variations in inputs. We allow firms to adjust wages in response to shocks to both efficiency and demand, as both of these represent measures of firm-level risk that may be passed on to workers' wages. We choose to estimate revenue TFP since it allows us to include firms from the service sector, which accounts for most of the Danish employment and economic activity.

[20]In Chan *et al.* (2019), we find that about 20% of the adjustments in labor inputs in response to productivity shocks are changes in the average labor input quality within the firm rather than changes in hours or number of employees.

A second possibility is to use the total wage bill of the firm. In this case, a firm that uses more engineers than janitors will have a larger wage bill, potentially controlling for the difference in ability of these types of workers. There are two main concerns with this approach. First, there is substantial evidence that firms play an important role in the determination of wages, and that workers with similar characteristics receive different wages in different firms.[21] Second, by using the wage bill as a measure of labor quality, we are implicitly assuming that labor markets are perfectly competitive, in which case we should not expect to see any passthrough from idiosyncratic TFP shocks to wages.

Hence, neither the number of workers in a firm nor the wage bill is an entirely satisfactory measure of the quality of the labor inputs hired by a firm. The estimates derived from our AKM model instead allow us to net out the effect of firms on the wage bill without imposing any conditions on the structure of the labor market that induces the distribution of wages we observe in the data. In particular, the estimated value of the individual fixed effect and observable characteristics from Equation (1), $\hat{\alpha}_i + X_{it}\hat{\Gamma}_t$, is a measure of the "quality" of the worker, which is independent from the characteristics of the firm that employs the worker (which are captured by the firm-time fixed effect, $\psi_{j(i,t)t}$). Using this measure for all workers in a particular firm, we define the *ability-adjusted labor input* as

$$A_{jt} = \sum_{i \in J_t} \exp\left(\hat{\alpha}_i + X_{it}\hat{\Gamma}_t\right) H_{ijt},$$

where J_t is the set of workers in firm j in period t, and H_{ijt} is the number of hours worked by individual i in firm j in period t.

Our ability-adjusted measure of firm productivity then comes from estimating

$$y_{jt} = f(k_{jt}, a_{jt}, m_{jt}) + \nu_{jt}, \tag{4}$$

where $a_{jt} = \log A_{jt}$. Note that the estimation procedure allows a_{jt} to be correlated with productivity ν_{jt} via η_{jt} and ω_{jt-1} but not ϵ_{jt}.

[21] For instance, several papers using the AKM approach find that around 10% of the dispersion of workers' wages is accounted for by fixed differences across firms. See for instance Barth *et al.* (2016), Song *et al.* (2019), and Engbom and Moser (2018).

3.3 Selection Model

Our main empirical analysis focuses on the impact of firm shocks on wages for workers that maintain a stable employment relationship with their firm. However, a worker's decision to stay in a firm is obviously endogenous and may depend on the shocks affecting the firms. Ignoring this endogenous selection in the sample of "stayers" will likely lead to biased passthrough estimates. For instance, suppose that after a negative shock a firm decides to cut wages in order to reduce costs. If workers are more likely to leave a firm when faced with large wage cuts, then focusing only on those workers who stay—and thus, are less likely to face a large wage drop—would bias our estimates toward zero, thereby overstating the degree of insurance provided by the firm.

In order to correct for this bias, we consider a standard selection model, as in Heckman (1979). In particular, the probability of staying in a firm between periods is given by $Pr(D_{ijt} = 1) = \Phi(U\delta)$, where $D_{ijt} = 1$ if worker i remains at firm j and U is a vector of worker and firm observables. We follow a standard two-step procedure by obtaining estimates of $\hat{\delta}$ and computing the inverse Mills ratio, denoted by $\hat{\lambda}$, which we include in our passthrough regressions. Our identification strategy relies on having a reasonable exclusion restriction for the first-stage regression that includes observable variation in U which determines the probability that workers will stay or leave their firm, but does not affect the growth rate of workers' wages should they choose to stay at the firm in that period.

We obtain this variation by using the family linkages available in our data to create, for each worker, a set of time-varying marital status indicators and—for those with working spouses—measures of their spouse's employment status and firm shocks. Specifically, we include indicators for marriage status, separation, change of spouse, and whether or not the individual's spouse is working if married. This last term is interacted with other spousal information, including the log wage, change in log wage, firm TFP and log TFP change, age, experience, and whether or not the spouse stayed in their firm for that period. We exclude information about the spouse of a worker if the couple is working at the same firm. This gives us the following first-stage probit model

$$\Pr(D_{ijt} = 1) = \Phi\left(\beta_p^d x_{ijt} + \beta_n^d x_{ijt} \times \mathbb{I}_{x_{jt}<0} + X_{it}\Omega^d + Z_{jt}\Gamma^d + T_{it}\Omega^d + E_{it} \times S_{it}\Psi^d\right), \tag{5}$$

where x_{ijt} is a measure of firm productivity shocks, X_{it} and Z_{ijt} matrices containing worker- and firm-level observables respectively, T_{it} is the set of marital status indicators, E_{it} is an indicator that

Table III – First-Stage Probit Estimates for Selection Model

Variable	Pr(Staying in Firm)	
	(1) Productivity Growth, $\Delta\nu_{jt}$	(2) Persistent Shock, η_{jt}
$\Delta\nu_{jt}$	.028*** (.005)	
$\Delta\nu_{jt} \times \mathbb{I}_{\Delta\nu_{jt}<0}$	.977*** (.004)	
η_{jt}		.313*** (.006)
$\eta_{jt} \times \mathbb{I}_{\eta_{jt}<0}$		1.111*** (.004)
Age	-.003*** (.001)	-.004*** (.001)
Male	-.132*** (.002)	-.154*** (.002)
Lag Tenure	.040*** (.000)	.040*** (.000)
Married	.027*** (.003)	.026*** (.003)
Change Spouse	-.119*** (.011)	-.119*** (.012)
Spouse's Firm's TFP (ν_{jt})	.017*** (.004)	.011*** (.004)
Spouse Stayer	.028*** (.003)	.026*** (.003)
Obs. (Millions)	7.04	7.04

Notes: Table III shows a few selected parameter estimates from our first-stage probit model. $*p < 0.1, **p < 0.05, ***p < 0.01$. Robust standard errors are clustered at the firm-level.

equals 1 if the worker's spouse is employed, and S_{it} is a vector of observables for the spouse and the spouse's firm, as described above. The assumption for our choice of instruments is that when a worker changes their marital status or their spouse has an income or employment change, this will affect the worker's decision of whether or not to keep working at the current firm. However, changes in marital status, spouse's employment, or spouse's wages do not affect the elasticity of wages to productivity in their own firm.

Column (1) of Table III shows a few key parameter estimates from the first stage mobility regressions (Equation 5) using TFP growth, $\Delta\nu_{ijt}$, to measure of a firm's shocks. Two results are worth mentioning. First, we find that positive productivity shocks increase a worker's probability of staying at the firm, whereas negative shocks decrease a worker's probability of staying. Second, we find that males, older workers, and workers who have recently changed spouses are more likely

to leave a firm, while being married, having longer tenure, having a spouse who stays at their firm, and having a spouse who experiences a positive TFP shock increase the probability of staying. Column (2) of Table III displays similar results if we replace $\Delta\nu_{jt}$ by the persistent shock to firms productivity, η_{jt}. In the next section, we use these estimates—the inverse Mills ratio in particular—to correct for the endogenous selection of stayers.

4 The Passthrough from Productivity Shocks to Wages

In this section, we discuss our main results relating the changes in workers' hourly wages to different measures of idiosyncratic firm productivity shocks. Table IV shows selected statistics for the main variables we use in our analysis. Panel A shows moments regarding the distribution of the log hourly wage growth for our sample of workers. In our sample, the standard deviation of log wage growth for stayers is 0.18 (column 1), which is half of the dispersion in wage growth for switchers (column 2).[22] Panel B shows similar statistics for the employment-weighted distribution of firm TFP growth, and the distribution of the persistent and transitory shocks to firm productivity. The standard deviation of the persistent component is equal to 0.27, which is larger than the standard deviation of the transitory component.[23] Panel C shows the same statistics as Panel B, but at the firm-level (not employment weighted). In the analysis below, we use the moments from this final panel to calculate the monetary impact of a one standard deviation shock to productivity.

Our main passthrough estimates are based on a series of worker-panel regressions that relate the change in workers' hourly wages to firms' idiosyncratic productivity shocks. More precisely, our baseline specification is

$$\Delta\hat{w}_{ijt} = \alpha + \beta^{\nu}\Delta\nu_{jt} + Z_{jt}\Gamma + X_{it}\Omega + \rho\hat{\lambda}_{ijt} + \delta_t + \zeta_{ijt}, \tag{6}$$

where $\Delta\hat{w}_{ijt}$ is the change in the ability-adjusted log hourly wage of individual i in firm j—defined in Equation (2)—between periods t and $t-1$, and $\Delta\nu_{jt}$ is the change in the log TFP for firm j between periods t and $t-1$. The matrices Z_{jt} and X_{it} control for firm characteristics (e.g., lagged

[22] By comparison, Kurmann and McEntarfer (2019) report an interquartile range of 11 log points which is close to our estimate of 13 long points. Relative to these authors, however, we find a much larger share of stayers who receive a wage cut.

[23] By comparison, Guiso and Pistaferri (2020) report a standard deviation of firms' persistent shocks of 0.05. As we show in this section, the passthrough estimates are quite in line with the rest of the empirical literature, indicating that in our context, firms provide a larger degree of insurance.

Table IV – Summary Statistics for Hourly Wage and Productivity Shocks

	Panel A: Workers		Panel B: Workers			Panel C: Firms		
	Δw_{ijt}		$\Delta\nu_{jt}$	η_j	ϵ_{jt}	$\Delta\nu_{jt}$	η_j	ϵ_{jt}
	Stayers	Switchers	Stayers					
Mean	0.02	0.07	0.00	0.02	0.01	0.00	0.00	0.00
Sd	0.18	0.36	0.26	0.27	0.20	0.24	0.19	0.17
P10	-0.14	-0.30	-0.25	-0.27	-0.16	-0.23	-0.16	-0.17
P25	-0.05	-0.11	-0.12	-0.13	-0.07	-0.10	-0.08	-0.08
P50	0.01	0.06	0.00	0.00	0.01	0.00	0.00	0.00
P75	0.08	0.23	0.12	0.14	0.09	0.10	0.07	0.08
P90	0.18	0.46	0.26	0.34	0.18	0.22	0.19	0.17
Obs. (Millions)	6.47	0.56	6.47	6.47	6.47	0.57	0.57	0.57

Table IV shows the sample statistics for workers' log hourly wage growth (Panel A) and firms' productivity shocks (Panel B at the worker-level and Panel C at the firm-level). To avoid the disclosure of any sensitive information, for all percentiles, we report the mean of all observations *within* a percentile-band rather than individual observations at the percentile cutoff.

productivity, firm size, firm age, etc.) and worker characteristics (e.g., gender, age, tenure in the firm, wage level, ability, etc.), respectively, δ_t is a time fixed effect that controls for aggregate fluctuations in the economy, and ζ_{ijt} is the residual. We also include the estimated inverse Mills ratio, $\hat{\lambda}_{ijt}$, obtained from the first-stage estimates of Equation (5). As we show below, controlling for selection has important implications for the value of β^{ν}, our main parameter of interest, which measures the *average* passthrough elasticity from changes in firm productivity to wages.

Table V displays our main results. Column (1) shows that there is positive and significant passthrough from firms' TFP shocks to hourly wages. Quantitatively, this elasticity of 0.076 implies that a worker employed in a firm that experiences an increase in productivity of one standard deviation (about 0.24 log points in our sample) receives an increase in average hourly wages of 0.018 log points. This change amounts to $1,075 US dollars for the average full-time worker in Denmark (see the bottom panel of Table V) or about about 1.8% of their annual income.[24] Given that in a typical year around 20% of firms in our sample (which employ around 25% of all the workers in Denmark) experience a change in productivity of at least one standard deviation away from the mean, we conclude that idiosyncratic fluctuations in firm productivity represent an

[24]For this calculation, we multiply the value of β^{ν} times the standard deviation of firm productivity growth times the average annual wage of the workers in the corresponding sample.

important source of fluctuations in workers' income.

Our estimates of firm productivity allow us to separately analyze the passthrough of positive and negative productivity changes to wages. We do so by interacting $\Delta\nu_{jt}$ with an indicator variable that is equal to one if the corresponding change is negative, as in the following specification:

$$\Delta\hat{w}_{ijt} = \alpha + \beta_p^\nu \Delta\nu_{jt} + \beta_n^\nu \Delta\nu_{jt} \times \mathbb{I}_{\Delta\nu_{jt}<0} + Z_{jt}\Gamma_t + X_{jt}\Omega_t + \rho\hat{\lambda}_{ijt} + \delta_t + \zeta_{ijt}, \tag{7}$$

where β_p^ν measures the average passthrough from a positive change in ν_{ijt}, while $\beta_p^\nu + \beta_n^\nu$ is the average passthrough from a negative change in ν_{ijt}. The results are shown in column (2) of Table V. First, notice that the coefficient for a positive change is slightly smaller than the average elasticity displayed in column (1), but still statistically and economically significant. Second, and more importantly, the elasticity of wages to a negative change in productivity is significantly higher and equal to 0.11. This indicates that a one standard deviation change in TFP, conditional on this change being negative, generates a decrease in annual wages for the average Danish worker of \$1,600 US dollars, which is roughly twice the change in wages resulting from a positive productivity shock of the same magnitude. In other words, the passthrough from firms' shocks to wages is not only significant, but also asymmetric, with negative changes in firms' idiosyncratic productivity generating much larger declines in wages than positive changes in productivity. We refer to this as "negative asymmetric" passthrough.

Transitory and Persistent Shocks

We then turn to analyzing the impact of transitory and persistent shocks to productivity on wages. These two types of shocks can have a distinct impact on workers, as firms might be more likely to insure workers from variations in productivity that are perceived as transitory—e.g., a decline in sales because of unexpected bad weather or the recent COVID pandemic—than from variations that are perceived as persistent—e.g., an increase in sales due to the implementation of a new online platform. Following the estimation approach introduced first by Guiso *et al.* (2005), most papers have consistently found that persistent shocks to firms have a significant impact on wages, whereas transitory shocks do not have a significant effect on wages (see Card *et al.* (2018) and Guiso and Pistaferri (2020) for recent reviews).[25] Here, we reevaluate the role

[25]One notable exception is Howell and Brown (2019), who find that a transitory cash flow shock to the firm significantly impacts workers' wages. The transitory shocks we study, however, differ from theirs in that a transitory cash flow can imply a persistent change in productivity if it leads to innovation, the purchase of new equipment, or the incorporation of new technologies.

Table V – Passthrough from Firm TFP shocks to Wages

Dep. Variable	Change in Log Hourly Wages, $\Delta\hat{w}_{i,j,t}$							
	Selection Corrected				Uncorrected			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Specification:	All	Pos/Neg	All	Pos/Neg	All	Pos/Neg	All	Pos/Neg
$\Delta\nu_{jt}$	.076***	.060***			.046***	.062***		
	(.004)	(.004)			(.003)	(.004)		
$\Delta\nu_{jt} \times \mathbb{I}_{\Delta\nu_{jt}<0}$		.053***				−.032***		
		(.005)				(.005)		
η_{jt}			.077***	.061***			.033***	.044***
			(.007)	(.004)			(.004)	(.004)
$\eta_{jt} \times \mathbb{I}_{\eta_{jt}<0}$				.070***				−.022***
				(.007)				(.009)
ϵ_{jt}			.034***	.025***			.034***	.032***
			(.003)	(.005)			(.003)	(.004)
$\epsilon_{jt} \times \mathbb{I}_{\epsilon_{jt}<0}$				.018**				.007
				(.008)				(.009)
$Mills_{it}$	−.219***	−.278***	−.188***	−.262***				
	(.014)	(.015)	(.023)	(.013)				
R^2	.78	.78	.79	.79	.78	.78	.78	.78
Obs. (M)	6.47	6.47	6.47	6.47	6.47	6.47	6.47	6.47
Monetary Value of a Shock to Firm TFP (US$ 2010)								
$\Delta\nu_{jt}$	$1,075				$655			
$\Delta\nu_{jt} > 0$		$840				$873		
$\Delta\nu_{jt} < 0$		$1,579				$403		
η_{jt}			$873				$386	
$\eta_{jt} > 0$				$689				$504
$\eta_{jt} < 0$				$1,495				$252
ϵ_{jt}			$336				$353	
$\epsilon_{jt} < 0$				$252				$319
$\epsilon_{jt} > 0$				$436				$386

Table V shows a set of OLS panel regressions controlling for firm and worker characteristics. All regressions include firm-level controls (which include firm age, lagged firm TFP level, firm employment, and total firm ability), worker-level controls (which include, a polynomial in age, lagged worker experience, lagged log wage level, lagged tenure in the firm, gender, and lagged log ability), the inverse of the Mills ratio to control for selection, and year fixed effects. $*p < 0.1, **p < 0.05, ***p < 0.01$. Robust standard errors are clustered at the firm-level.

of persistent and transitory shocks by including in our baseline specification the persistent and transitory components of firm productivity estimated in Section 3.2. In particular, we estimate

$$\Delta\hat{w}_{ijt} = \alpha + \beta^{\eta}\eta_{jt} + \beta^{\epsilon}\epsilon_{jt} + Z_{jt}\Gamma_t + X_{it}\Omega_t + \rho\hat{\lambda}_{ijt} + \delta_t + \zeta_{ijt}, \tag{8}$$

where β^{η} and β^{ϵ} are the elasticity of wages with respect to the persistent and transitory components of firms' TFP, respectively.[26] Column (3) of Table V shows the results. We find that both transitory

[26] We estimate a separate first-stage model for every regression specification in this paper, depending on the firm shocks and the sample in question. In this case, we estimate $\hat{\lambda}_{ijt}$ from a separate first-stage regression on η_{jt} and ε_{jt} rather than $\Delta\nu_{jt}$.

and persistent shocks have a significant impact on hourly wages, although wages are greater than two times more responsive to persistent than to transitory productivity shocks.

We then separate the impact of transitory and persistent shocks into their positive and negative parts, as we do for total productivity in Equation 7. We similarly find a marked asymmetry between positive and negative shocks. In fact, as column (4) shows, the elasticity of wages to a negative persistent shock is twice as large as the elasticity to a positive persistent shock. In terms of annual earnings, a decline in η_{jt} of one standard deviation generates a loss of $1,495 US dollars, whereas an increase in η_{jt} of the same magnitude generates an increase in annual earnings of $689 US dollars. We find a similar negative asymmetric pattern for transitory shocks, with negative transitory shocks having a larger impact on wages than positive transitory shocks, although the magnitudes are much smaller than for persistent shocks.

Bias and Asymmetry

The evidence presented in Figure 1 suggests that the bias arising from endogenous worker mobility is large, significant, and asymmetric. In our context, selection bias will affect the passthrough estimates if the probability that a worker stays at their firm (and thus remains in our baseline sample for estimating within-firm passthrough) depends on the magnitude or sign of the firm shock. Intuitively, workers in firms that experience larger declines in TFP (and thus face larger declines in wages) may be more likely to leave their firm than workers in firms that experience smaller declines in TFP. In this case, we would expect our passthrough estimates for negative shocks to be biased toward zero.

To evaluate the extent of the bias, we repeat the previous analysis without correcting for worker selection (i.e., we exclude the inverse Mills' ratio from our regressions). The results are shown in columns (5) to (8) of Table V. As expected, we find that selection biases the impact of firms' shocks to hourly wages toward zero. We also find that the bias is more significant for persistent than for transitory shocks. To see this, we compare columns (3) and (7), where the elasticity to persistent shocks declines by half for persistent shocks when we do not control for selection, but remains the same for transitory shocks. This is consistent with the timing of our model of firm productivity, which assumes that inputs (including labor) are fixed prior to observing ϵ_{jt}. Consistent with the intuition above, the passthrough estimates for negative shocks are the most affected by selection: if we were to ignore selection, we would conclude that negative persistent shocks have a passthrough elasticity of 0.022, six times smaller than the elasticity implied

by our baseline selection-corrected estimates. Similarly, not controlling for selection biases the passthrough elasticity of total productivity changes from 0.11 down to 0.03. These results would lead us to wrongly conclude that passthrough is positive asymmetric. Given the importance of properly controlling for selection, all of the results that follow include selection-correction terms.

It is useful at this point to compare our results for Denmark to the estimates provided by the literature for other countries. Despite methodological differences, our main estimates are similar to those found by Guiso *et al.* (2005) using data from Italy, Fagereng *et al.* (2017) using data from Norway, and Lamadon *et al.* (2019) using data from the United States. Our results lie in the middle of the estimates presented by these authors. One important difference between the estimates presented by most papers in the literature, relative to ours, is that we find significant passthrough from transitory shocks, while other papers find very limited impact from transitory shocks on wages.

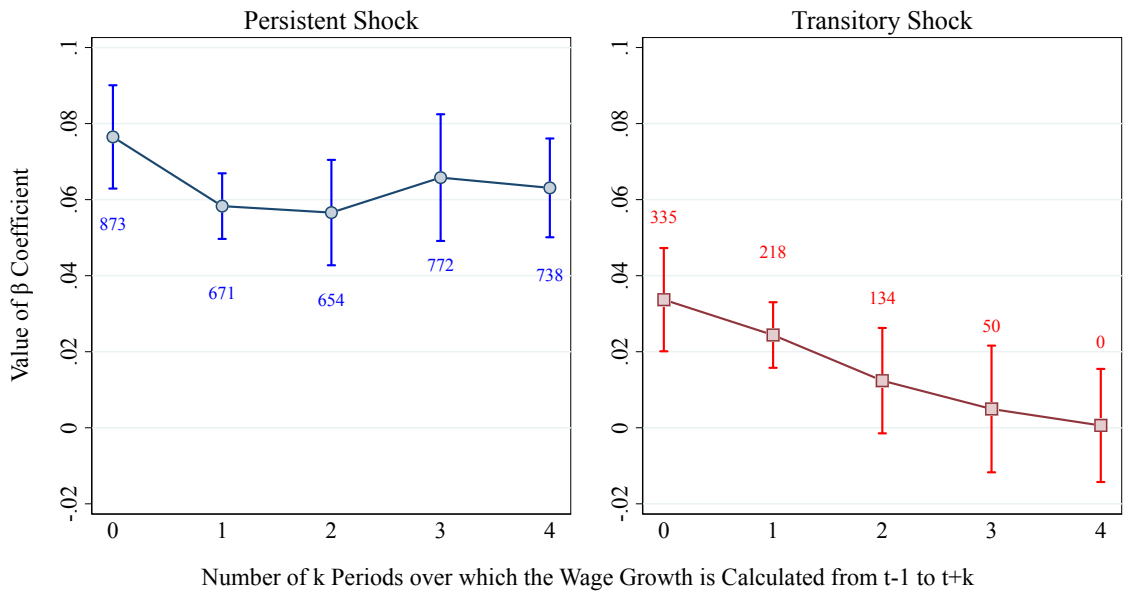
Few papers have studied whether negative and positive shocks have a differential impact on workers' wages. One such study is Juhn *et al.* (2018), who use US Census data and find mixed evidence on how positive and negative shocks to firm revenue affect wages. The main reason behind the differences between our estimates and theirs is that we correct for selection. As we noted earlier, not controlling for selection in our context biases the conditional elasticity of negative changes in total productivity to wages downward to 0.03, which is half the elasticity from a positive productivity change (see column (6) in Table V).

Persistence and Aggregate Shocks

We complement the previous analysis by studying, first, whether shocks to firms translate into persistent changes in workers' wages, and second, how the passthrough from idiosyncratic shocks to wages compares to the passthrough from industry or aggregate shocks.

We start by discussing the long-term impact of firms' shocks to workers wages. Intuitively, if shocks to firms only translate into a one-period increase in workers' wages (even when the shocks to firms are persistent), one should expect large contemporaneous passthrough (a positive and significant correlation between a shock in period t with a change in workers' wages between t and $t-1$), but less passthrough at longer horizons (a correlation between a shock to firms in period t and a wage change between $t+4$ and $t-1$ closer to 0). To study the persistence of passthrough, we modify our baseline specification in (8) by extending the horizon of the wage change on the left-hand side to $t+k$ periods, where k can take values between 0—as in our baseline case—and

Figure 3 – Shocks to Firms Have a Long-Lasting Impact on Workers' Wages



Note: Figure 3 shows the elasticity of hourly wages to a persistent (transitory) shock to firms productivity. Each point on the graph is the elasticity coefficient from a separate regression where the dependent variable the change in workers' hourly wages different time-horizons (defined by $k \geq 0$). The baseline case is given by $k = 0$. In each plot, the points represent the passthrough elasticity coefficient (β) from a separate second-stage regression, while the vertical lines show 95% confidence intervals around those point estimates. In each plot, the numbers above and below the lines represent the monetary value of a shock of one standard deviation calculated using the corresponding elasticity. All monetary values (in 2010 US$) are calculated relative to the average annual labor earnings within the corresponding group.

4. Importantly, we keep constant the period in which we measure firms' productivity shocks and other firm and worker observables.[27]

To simplify the exposition of our results, Figure 3 shows on the y-axis the elasticity of worker wages to a persistent or transitory shock to firm productivity at different horizons. Each point on the figure represents a passthrough coefficient from a separate set of first- and second-stage regressions. In both panels, the x-axis corresponds to the periods over which the wage growth is calculated and the vertical lines are 95% confidence intervals for the corresponding regression coefficient. The left panel shows that the passthrough from persistent TFP shocks is not only statistically significant in the first year—our baseline estimate—but also persists after 4 years, with only a small decay in magnitude. In contrast, short-lived transitory shocks have a much less persistent impact on workers' wages, although the effect does not disappear immediately, generating a small but still significant change in workers' wages, even 2 years after the shock.[28]

[27] Note that our selection correction procedure changes as well, such that we run separate first-stage regressions for each separate time horizon, where the dependent variable in the first stage is an indicator of whether the worker stayed at the firm for all $t-1$ to $t+k$ periods.

[28] As we show in Appendix A, these results are robust to separating positive from negative shocks (Panel A of Figure A.3) and restricting our sample to a balanced panel of workers who stay in the same firm for four years after the shock (Panel B of Figure A.3).

Table VI – Passthrough from Firm and Industry TFP shocks to Wages

Dep. Variable	Change in Log Hourly Wages, $\Delta\hat{w}_{i,j,t}$				
	(1)	(2)	(3)	(4)	(5)
	Industry and Aggregate Shocks		Switchers	Expansions	Recessions
Specification:	All	Pos/Neg			
$\Delta\nu^f_{jt}$	.076***	.058***			
	(.004)	(.004)			
$\Delta\nu^f_{jt} \times \mathbb{I}_{\Delta\nu_{jt}<0}$		.060***			
		(.006)			
$\Delta\nu^k_t$	.024***	.00			
	(.006)	.015			
$\Delta\nu^k_t \times \mathbb{I}_{\Delta\nu^k_t<0}$		.046*			
		(.023)			
η_{jt}			.025***	.056***	.014
			(.007)	(.004)	(.032)
$\eta_{jt} \times \mathbb{I}_{\eta_{jt}<0}$			.002	.080***	.127***
			(.002)	(.007)	(.041)
ϵ_{jt}			.057***	.025***	.032***
			(.010)	(.006)	(.008)
$\epsilon_{jt} \times \mathbb{I}_{\epsilon_{jt}<0}$			−.018	.021**	−.007***
			(.018)	(.009)	(.018)
$Mills_{it}$	−.209***	−.275***	−.012***	−.230***	−.333***
	(.014)	(.016)	(.003)	(.020)	(.035)
R^2	.78	.78	.70	.81	.44
Obs. (M)	6.47	6.47	0.55	4.2	1.1
	Monetary Value of a Shock to Firm TFP (US$ 2010)				
$\Delta\nu_{jt}$	$1,041				
$\Delta\nu_{jt} > 0$		$789			
$\Delta\nu_{jt} < 0$		$1,595			
$\Delta\nu^k_t$	$67.2				
$\Delta\nu^k_t > 0$		$0.0			
$\Delta\nu^k_t < 0$		$117			
$\eta_{jt} > 0$			$2,099	$638	$167
$\eta_{jt} < 0$			$1,914	$1,528	$1,662
$\epsilon_{jt} < 0$			$554	$252	$336
$\epsilon_{jt} > 0$			$369	$453	$269

Table VI shows a set of OLS panel regressions controlling for firm and worker characteristics. All regressions include firm-level controls (which include, firm age, lagged firm TFP level, firm employment, and total firm ability), worker-level controls (which include, a polynomial in age, lagged worker experience, lagged log wage level, lagged tenure in the firm, gender, and lagged log ability), the inverse of Mills ratio to control for selection, and year fixed effects. In column (4), expansion years are all years in our sample with the exception of 2002-2003 (which experienced a mild recession) and 2008-2009. The results for 2008 and 2009 are displayed in column (5). $*p < 0.1, **p < 0.05, ***p < 0.01$. Robust standard errors are clustered at the firm-level.

We conclude this section by studying the impact of aggregate and industry shocks on workers' wages. Separating their effect is important, as there might be general equilibrium effects that confound our passthrough estimates. To separate the effect of aggregate- and industry-level fluctuations in productivity, we follow Carlsson *et al.* (2015) and first regress our firm-level productivity changes on a set of year dummies and calculate the residual change, which is orthogonal to the aggregate cyclical variation in TFP. We then regress those residual changes on a full set of year-industry dummies. The predicted values from this regression give us our measure of industry-level TFP shocks (denoted by $\Delta\nu_t^k$), while the residuals are our orthogonal measure of idiosyncratic firm-level changes in TFP (denoted by $\Delta\nu_{jt}^f$).

Finally, we regress the change in log hourly wages on these measures of firm- and industry-level productivity shocks. As column (1) of Table VI shows, the elasticity of wages to firm-level shocks (after we have stripped out the year and industry components) is essentially the same as in our baseline results (column 1 of Table V), indicating that aggregate shocks play a minor role in our results. Changes in average productivity at the industry-level have a significant impact on workers' wages, although the passthrough is less than a third of the passthrough from idiosyncratic shocks. Furthermore, if we separate positive from negative shocks, we find that only negative industry productivity changes have an impact on workers' wages. The economic impact is small since there is little variation in the industry-level productivity, relative to the aggregate and idiosyncratic variation.

To summarize, in this section, we have shown that idiosyncratic shocks to firms' productivity have a significant and persistent impact on workers' wages, which depend not only on the nature of the shocks (persistent versus transitory) but also on the sign (positive versus negative). In the following sections, we complement these results in two ways. First, in Section 5, we discuss a few key theoretical mechanisms that rationalize the positive correlation of idiosyncratic shocks to firm productivity and worker wages. Second, in Section 6, we exploit the richness of our dataset to explore how passthrough varies across workers and firms with different characteristics, and over time.

5 Discussion and Theoretical Implications

The empirical results discussed thus far indicate that productivity shocks have significant, persistent, and asymmetric effects on hourly wages and that these effects can be very large, especially

for persistent negative shocks. These results, however, are difficult to interpret through the lens of a standard competitive model of the labor market, where atomistic firms are price-takers in input markets, and therefore, there is zero passthrough from firms' idiosyncratic shocks to workers' wages. Looking beyond the competitive benchmark, in this section we discuss three possible mechanisms that could account, at least in part, for the positive and asymmetric correlation between firm shocks and wages.

5.1 Labor Market Power

First, consider a simple departure from the competitive benchmark in which firms have some monopsony power in the labor market and face an upward sloping labor supply curve. Specifically, consider a profit-maximizing firm with production function $Y = Af(L)$, where $A > 0$ is the firm's idiosyncratic productivity and the production function is such that $f(L) > 0$, $f' > 0$, and $f'' < 0$. The firm faces a labor supply curve given by $L^s = g(w)$, where $w > 0$ is the real wage per unit of labor, and $g(w)$ is twice continuously differentiable with $g(w) > 0$ and $g' > 0$. Theorem 1 shows that under very general conditions, an increase in A generates an increase in w, that is, there is positive passthrough from firms' shocks to wages.

Theorem 1. *Under the preceding assumptions on A, w, f, and g, the elasticity of workers' wages with respect to firms' productivity shocks is positive, $\frac{dw}{dA}\frac{A}{w} > 0$, if either of the following two conditions holds: (a) $g'' \leq 0$, or (b) $g'' > 0$ and $d\phi(w)/dw > 0$ with $\phi(w) \equiv g(w)/g'(w)$.*

Proof. It is straightforward to show that the elasticity of w with respect to A is given by

$$\varepsilon_A^w \equiv \frac{dw}{dA}\frac{A}{w} = \left[w \left(\frac{2\left(g'(w)\right)^2 - g(w)\, g''(w)}{\left(\left(wg'(w) + g(w)\right) g'(w)\right)} - \frac{f''\left(g(w)\right) g'(w)}{f'\left(g(w)\right)} \right) \right]^{-1}. \tag{9}$$

Notice that the second term in the brackets is negative and the denominator of the first term is positive since $f' > 0, f'' < 0$, and $g' > 0$. A sufficient condition for our result to hold is that the numerator of the first term in brackets is positive. If $g''(w) \leq 0$, then this condition is trivially satisfied. If $g'' > 0$, a sufficient condition is that $d\phi(w)/dw > 0$. To see that this is the case, notice that

$$\phi'(w) = \left[\left(g'(w)\right)^2 - g(w)\, g''(w) \right] / \left(g'(w)\right)^2,$$

which implies that

$$\begin{aligned}\phi'(w) > 0 &\implies (g'(w))^2 - g(w)\,g''(w) > 0 \\ &\implies 2\,(g'(w))^2 - g(w)\,g''(w) > 0 \\ &\implies \varepsilon_w > 0,\end{aligned}$$

which gives us our result.[29] □

Any non-constant labor supply curve will imply some degree of passthrough. The intuitive interpretation of Theorem 1 is that the passthrough elasticity will be *positive* on any part of the labor supply curve that is *increasing* and not *too convex* in wages.[30] A corollary of this theorem is that as long as the labor supply curve is not log-linear in wages (i.e., as long as it does not take the form $L^s = w^\theta$ for some $\theta > 0$), the passthrough elasticity will also be asymmetric, in that a discrete positive change in productivity will generate either a larger or smaller change in wages than a negative change of the same magnitude in percentage terms. This is a result of the passthrough elasticity being a function of the wage level. However, it is difficult to know the direction (positive versus negative) of this asymmetry without further assumptions on the supply curve.

To gain further intuition, we consider a particular but still quite general case in which the production function is given by $f(L) = L^\alpha$ with $\alpha \in (0,1)$, and the labor supply is given by $L(w) = w^\theta + \beta$ with $\beta \leq 0$ and $\theta > 0$. Notice that, depending on the value of θ, the function $L(w)$ can be strictly concave ($\theta < 1$) or convex ($\theta > 1$). The passthrough elasticity in this case is given by

$$\varepsilon_A^w = \left(\frac{(\theta+1)w^\theta + (1-\theta)\,\beta}{(\theta+1)w^\theta + \beta} + \frac{\theta(1-\alpha)w^\theta}{w^\theta + \beta}\right)^{-1},$$

which is always positive for $\theta > 0$ and $L(w) > 0$. In this simple case, the passthrough is asymmetric (since the elasticity depends on the wage level), with more passthrough of positive productivity changes than negative changes. Proposition 2 states this result formally.

[29] See Appendix D for more details and a derivation of ε_w.

[30] Note that the conditions in the theorem are actually stronger than they need to be, since ε_w will be positive for $\phi'(w) < 0$ as long as $\frac{2\left(g'(w)\right)^2 - g(w)g''(w)}{((wg'(w)+g(w))g'(w))} > \frac{f''(g(w))g'(w)}{f'(g(w))}$.

Proposition 2. *Given a labor supply curve of the form $L(w) = w^{\theta} + \beta$ with the preceding assumptions on f, β, and θ, the passthrough elasticity is positive and increasing in $\log A$, so that a positive discrete change in productivity generates a greater change in wages than a negative discrete change in productivity of the same magnitude.*

Proof. See Appendix D. □

It is clear that a simple model of labor market power can generate some of the patterns we see in the data. In particular, under general conditions, we find positive passthrough which may display either positive or negative asymmetry.[31] The data generated from a dynamic version this model would also exhibit the same selection problem that we discuss above, as firms that reduce wages due to negative productivity shocks would also shed some of their incumbent labor, while firms that increase wages due to positive shocks would maintain their incumbent workers. It is not immediately clear what conditions on the labor supply curve would have to exist in order to generate the negative asymmetric we find in the data, as a simple parameterization of the above model implies positive asymmetry (i.e., the passthrough elasticity for positive shocks is great than for negative shocks).

One additional prediction of this simple model is that as long as the labor supply curve is not log-linear, passthrough will differ for firms which are on different points on their labor supply curve. In particular, one can decompose the passthrough elasticity into the component due to the effect of productivity on labor requirements, and the effect of changes in labor requirements on the wage. Formally, the passthrough elasticity is

$$\varepsilon_A^w = \frac{dw}{dA}\frac{A}{w} = \frac{dw}{dL}\frac{L}{w}\frac{dL}{dA}\frac{A}{L} = \frac{\varepsilon_A^L}{\varepsilon_w^L} \tag{10}$$

where ε_A^L is the elasticity of labor with respect to firm productivity, and ε_w^L is the labor supply elasticity. This implies that the passthrough elasticity is inversely related to the labor supply elasticity, such that firms facing lower labor supply elasticities will have higher passthrough elasticities. Given that optimal wages in this setting are given by a markdown from marginal productivity, such that $w = \mu MPL$ where $\mu = \frac{\varepsilon_w^l}{\varepsilon_w^l + 1}$, we also should see that firms with greater market power (greater wage markdowns) exhibit higher degrees of passthrough. The general intuition is that firms which are more productive, or have greater labor market power (due to high amenity values

[31] Note that the direction of asymmetry in Proposition 2 does not depend on the degree of decreasing returns to scale, α.

of work at that firm for example), will tend to be larger and thus further up their supply curve. If passthrough is increasing in productivity (as in the example above), we should expect to see that larger and more productive firms exhibit higher passthrough, and that passthrough is positive asymmetric. Alternately, if passthrough is decreasing in productivity, we should see negative asymmetric passthrough and less passthrough from larger and more productive firms. We test these implications in the next section.

5.2 Financial Constraints

Several studies have suggested that financial constraints might account for the positive passthrough from firm shocks to wages. The starting point is a basic theory of the firm—perhaps dating back to Knight (1921)—which suggests that the intrinsic role of firms is to provide insurance to workers: firms are more able to hedge against risk, thus allowing them to insulate workers from shocks. However, the ability of a firm to insure its workers against market risk will depend on that firm's ability to insure itself. For example, an aggregate shock that tightens a firm's borrowing constraint reduces its ability to insure its workers against idiosyncratic productivity shocks, more so for young or small firms which are potentially more constrained than old and large firms.

Intuitively, firms that are more financially constrained should be more likely to pass negative productivity shocks on to their workers, while less financially constrained firms will be better able to insure workers against such shocks. Larger shocks are also more likely to push a firm up against its constraints than smaller shocks, so we should see significantly more passthrough for larger (negative) shocks than for positive shocks. We test these implications directly in the following sections.

In an important contribution, Michelacci and Quadrini (2009) study the relationship between financial constraints and firm wage policies in a model in which firms can commit to long-term wage contracts. Two key predictions arise from their model: first, future firm growth is negatively correlated with the wages of new hires, and second, wage growth for incumbent workers (stayers) is positively correlated with firm growth. In their model, firms find it profitable to commit to backloaded wage profiles since at least part of the capital accumulated by the firm is embodied in the worker in the form of recruiting costs or firm-specific human capital. Hence, firms "borrow" from their workers to increase their short-run growth rate. Workers, however, cannot commit to stay in the firm, and therefore, wages do not decrease—the worker can always leave and obtain the

market rate. Thus, one should expect zero passthrough from negative growth to wages for stayers, which is somewhat at odds with our main results.

5.3 Search Frictions

Imperfections in the labor market originating from search frictions may also rationalize positive passthrough from firm productivity shocks to wages. Consider for instance a search and matching model in which the value of the match is split between firms and workers using a sequential auction protocol, as in Postel-Vinay and Turon (2010) or Lise, Meghir and Robin (2016). Workers are heterogeneous in their fixed type p, whereas firms differ in their productivity ε, which varies over time. We denote the surplus generated by the firm-worker match by $S(\varepsilon, p)$ and the worker's valuation of the match by $V(\varepsilon, p)$. The worker's wage contract is denoted by $\omega(r, p)$, which depends on the worker type p, the worker's negotiation baseline r, and is defined as follows

$$\omega = \omega(r, p) \Leftrightarrow V(\phi, p) = V_0(p) + S(r, p) \Leftrightarrow \Pi(\varepsilon, \omega, p) = S(\varepsilon, p) - S(r, p),$$

where $V_0(p)$ is the worker's lifetime value of unemployment, and Π denotes firm profits.

Suppose the output from a match takes the form: $y_t = p\varepsilon$, and consider the case in which the firm gets a shock that moves its productivity to ε' such that $\varepsilon_{min} \leq \varepsilon' < r$, where ε_{min} represents the lowest productivity level at which the match generates a positive surplus. The first part of the inequality ensures that the match is still viable, so $S(\varepsilon', p) > 0$ and workers and firms benefit from maintaining this match. The second inequality, however, indicates that profits are negative at the current wage schedule $\omega(r, p)$, since $S(\varepsilon', p) - S(r, p) < 0$. Firms are thus better off firing the worker rather than maintaining the match at the original wage level, and therefore, have a credible threat to force a renegotiation of the wage contract. As long as $V(\varepsilon', p)$ is greater than the value of unemployment, workers will be willing to accept a lower wage rate at $\omega(\varepsilon', p)$. Hence, the passthrough elasticity of workers' wages with respect to firms' idiosyncratic productivity is given by

$$\frac{dw}{da}\frac{A}{w} = \frac{\omega(\varepsilon', p) - \omega(\varepsilon, p)}{(\varepsilon' - \varepsilon)\omega(\varepsilon, p)}\varepsilon,$$

which is greater than 0, but less than 1, i.e., the firm provides some insurance to workers.

Two important implications of the model are worth mentioning. First, without further assumptions, the model will have difficulty producing the passthrough of positive productivity shocks that

we find in the data. To see this, consider a firm that receives a positive change in productivity, such that $\varepsilon' > \varepsilon$. In this case, firms do not have any incentive to renegotiate wages, while the workers cannot force wage renegotiation and obtain rents from this positive shock unless they receive a competing outside offer at the same time, or an increase in the value of the option of looking for another job.

Second, we should expect size dependance in the passthrough of negative shocks: small changes in productivity that do not trigger a renegotiation should have almost no impact on the wage rate, whereas large productivity shocks should command a higher passthrough. To see this, consider a small negative productivity shock such that $r < \varepsilon' < \varepsilon$ so that the shock is above the worker's negotiation threshold. In this case, the negative shock to productivity does not generate a decline in the worker's wages, as the firm is not able to make a credible threat of firing the worker and forcing the a wage renegotiation. Note that, like in the monopsony power model, the data generated from this model will also suffer from the selection bias problem we find, as large negative shocks will induce separation, while smaller and positive shocks will not. As with the other two theoretical frameworks, we are able to test the implications of the basic search friction model directly from the data in the following sections.

6 Heterogeneous Passthrough

As we have shown, the average passthrough from firm shocks to wages is significant and asymmetric. Still, it is possible that the overall effect masks substantial heterogeneity across worker and firm types. For example, it is possible that workers of different ability, age, or tenure are subject to different passthrough, which we analyze in Section 6.1. Similarly, in Section 6.2, we study whether firms with different productivity or size pass shocks to their workers at different rates. Finally, in Section 6.3 we analyze whether passthrough is state dependent and changes with aggregate economic conditions. The main conclusion of this section is that the passthrough from firms' shocks to wages is highly heterogeneous and varies substantially across workers and firms groups, and over the business cycle.

6.1 Worker Heterogeneity

Wages and Ability

We first study whether workers at different income levels are differentially exposed to shocks affecting the firms where they work. Studying how the passthrough varies across the income distribution is important for at least two reasons. First, low-income workers are more likely to be credit constrained. Then, to the extent that idiosyncratic shocks to firms represent an uninsurable risk, finding a higher passthrough for low-income workers might have significant welfare implications, even though the average passthrough is small. Second, variations in the passthrough across income levels might help explain why individuals at the top and bottom of the income distribution seem to face larger fluctuations in labor earnings than individuals in the middle of the income distribution (Guvenen *et al.*, 2015). Overall, we find that high-wage and high-ability workers are more exposed to idiosyncratic shocks to firms' productivity than low-wage and low-ability workers.

We start by separating workers into quintiles based on their past hourly wage and estimate the passthrough from persistent and transitory shocks within each quintile. Panel A of Figure 4 summarizes our results. The differences in passthrough between low- and high-wage workers after a persistent shock to the productivity of their firms are substantial: the elasticity of hourly wages to a persistent positive shock to firms' TFP for workers in the fifth quintile of the distribution is more than twice as large as the elasticity for workers in the first quintile. Quantitatively, we find that workers at the fifth quintile of the distribution gain six times more in annual income than workers at the bottom quintile ($1,763 versus $285, or 1.9% and 0.8% of the within-group average annual income, respectively) when their firms receive a persistent shock to firms' TFP of one standard deviation.

As we discussed earlier, the passthrough from negative persistent shocks to firms' productivity on workers' wages is stronger than the passthrough from positive persistent shocks. We find this to hold for all workers, independent of their income level, but especially for workers at the top quintile. For this group of workers, a negative shock to the persistent component of firm productivity generates a drop in annual wages of $3,207 (or about 3.4% of the average annual income for that group). In contrast, the annual wages for workers in the first quintile only decline by $400. In other words, high-wage workers experience larger gains and losses than low-wage

workers, both in terms of total and percentages of income when their firms experience persistent TFP shocks. This is is consistent with the idea that workers' compensation is increasingly linked to firm performance as workers move up the income distribution.

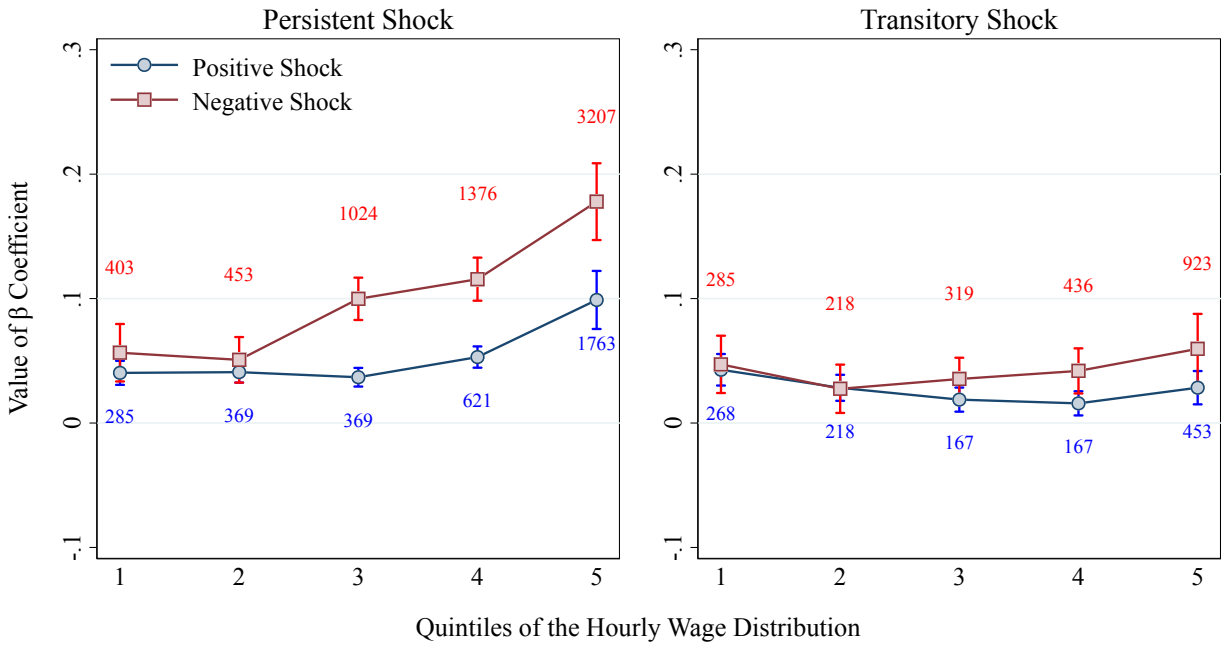
Consistent with our baseline estimates, the quantitative effect of transitory shocks to TFP is considerably smaller than the effect of persistent shocks, as the top-right panel of Figure 4 shows. We do not find statistically significant differences between the passthrough of transitory shocks across the income distribution, although the quantitative impact is larger for workers in the fifth quintile than for workers in the first quintile (compare \$923 to \$285 in the case of a negative shock). These differences are mainly driven by differences in the annual earnings of each group rather than by the responsiveness of hourly wages to firm productivity shocks.

One potential concern about the results shown in panel A of Figure 4 is that labor earnings and productivity show strong mean reversion, possibly confounding the real impact of firms' shocks to wages, especially for those workers and firms at the top and bottom of the corresponding distributions. To address this concern, we analyze how passthrough changes across workers of different "ability", where ability is defined as the sum of a worker's fixed effect and time-varying observable characteristics, $\exp(\hat{\alpha}_i + \hat{\Gamma} X_{it})$, as measured by our AKM estimates from Section 3.1. As before, we separate workers in quintiles of the ability distribution and run our baseline regression within each group. Panel B of Figure 4 summarizes these results. Similar to the patterns observed across the income distribution, we find that workers at the top of the ability distribution are subject to a higher passthrough. Specifically, we find that workers at the fifth quintile receive an increase of \$1,444 (1.7% of their average annual income) after a positive persistent shock to firms' productivity of one standard deviation, whereas workers in the first quintile gain only \$335. As for negative persistent shocks, we find an increasing trend as we move to higher ranks of the ability distribution: workers at the top ability quintile lose, on average, \$2,149 (2.5% of their annual income) in response to a one standard deviation negative persistent shock while, those at the bottom quintile lose \$520 (1.3% of their annual income).[32] Relative to the passthrough from persistent shocks, the passthrough from transitory shocks is much smaller in magnitude and does not change much across the ability distribution (bottom right panel of Figure 4).

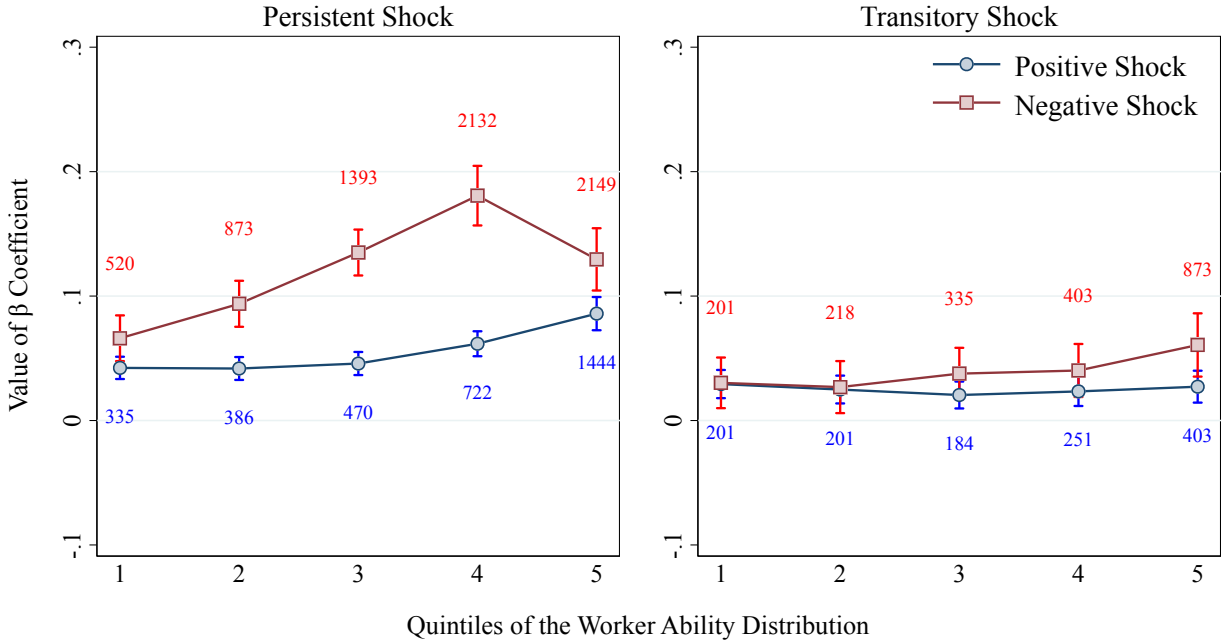
[32]Notice that although the passthrough elasticity is lower for workers at the fifth quintile, relative to those in fourth, the monetary values are almost identical.

Figure 4 – Passthrough Across the Worker Income and Ability Distributions

(a) Lag Hourly Wages



(b) Measured Ability



Note: Panel A of Figure 4 shows the elasticity of hourly wages with respect to firms' productivity within quintiles of the workers' lag hourly wage distribution. Panel B shows the elasticity within quintiles of the workers' ability distribution measured by $\exp(\hat{\alpha}_i + \hat{\Gamma} X_{it})$ derived from our AKM estimates. In each plot, the points shows the passthrough elasticity coefficient (β) from a separate second-stage regression, while the vertical lines show 95% confidence intervals around those point estimates. In each plot, the numbers above and below the lines represent the monetary value of a shock of one standard deviation calculated using the corresponding elasticity. All monetary values (in 2010 US$) are calculated relative to the average annual labor earnings within the corresponding group.

Tenure and Age

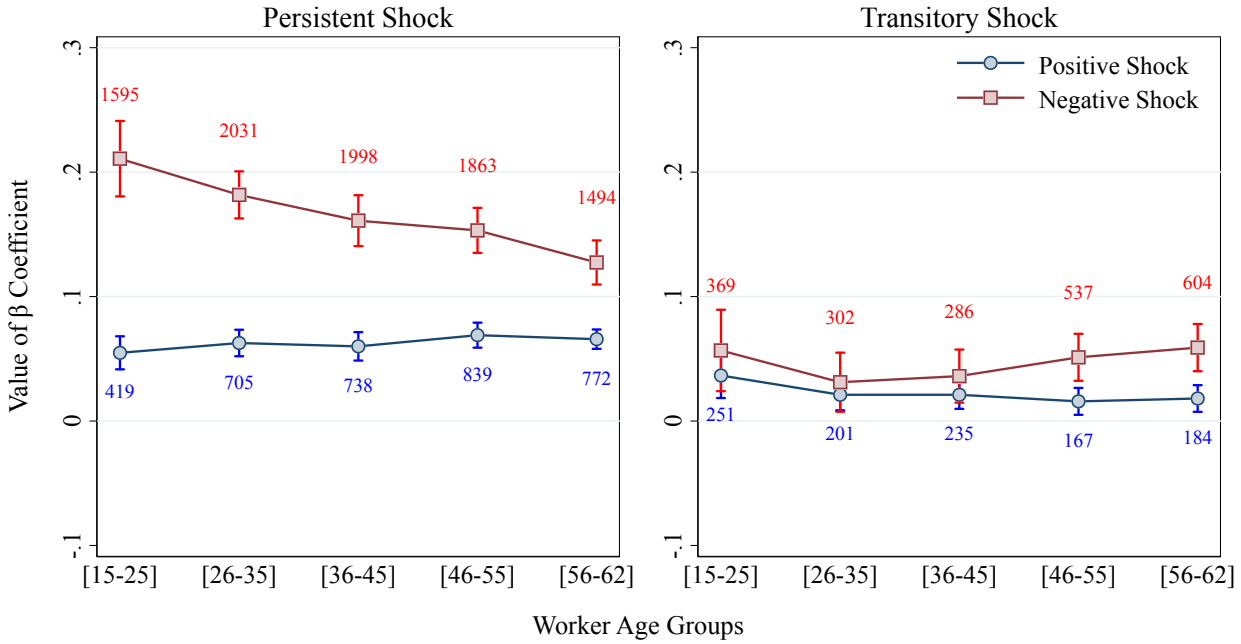
Workers may be more or less exposed to firm shocks, depending on their age and tenure within the firm. For instance, older workers are more likely to have accumulated general work experience, have differing tenure-contingent contracts, or have accumulated specific human capital that is valuable for the firm and difficult to replace. In such cases, the firm may try to insure such older and long-tenure workers from negative shocks more than younger and newer workers. Alternatively, workers with longer tenure might receive a higher increase in earnings after a positive productivity shock, relative to a younger worker, if the firm implicitly "borrowed" from them (Michelacci and Quadrini, 2009). Our results are consistent with this intuition. As we show below, our estimates indicate that, relative to younger and newer workers, older and long-tenure workers experience higher gains from persistent positive shocks and lower losses from persistent negative shocks to firms' productivity. The opposite is true, however, for transitory shocks as young and short-tenure workers enjoy higher gains from positive shocks but lower losses from negative shocks.

Panel A of Figure 5 shows the elasticity of wages to a persistent and a transitory shock to firms' productivity for workers in different age groups. Three features of the figure are worth noticing. First, the passthrough from persistent positive shocks is weakly increasing in terms of worker's age. This implies that older workers get a higher wage increases than younger workers when firms receive a positive TFP shock, although the difference is not large. For instance, workers who are between 56 and 62 years old receive an average increase in their annual income of \$772 (or 1.3% of their annual earnings) when firms experience a one standard deviation positive shock, whereas workers who are 25 years old or younger gain \$419 (or 1.1% of their annual earnings) in response to a persistent TFP shock of the same magnitude and sign.

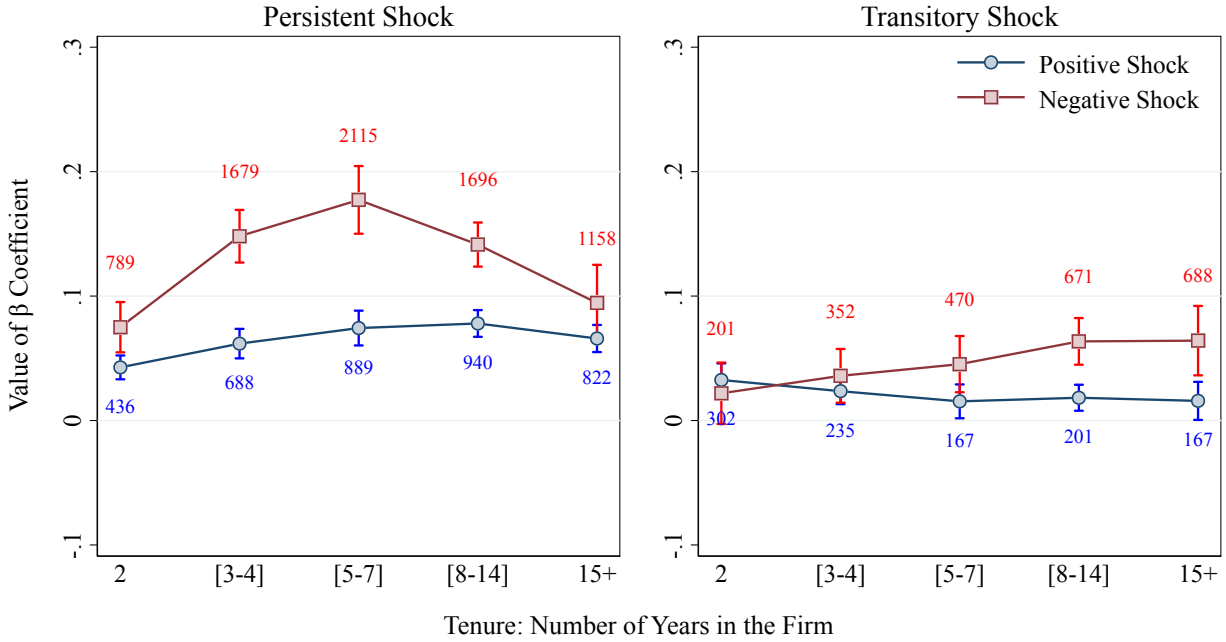
Second, the response of wages to a negative persistent TFP shock is larger than the response to positive shocks and decreases monotonically with workers' age. For instance, workers who are 56 or older lose \$1,494 on average in response to a one standard deviation negative shock to persistent TFP (a 2.5% decrease in annual income), whereas workers who are 25 years old or younger lose \$1,595 on average after a shock of the same magnitude (3.4% of their annual income).

Figure 5 – Passthrough by Workers' Age and Tenure

(a) Workers' Age



(b) Workers' Tenure



Note: Panel A of Figure 5 shows the elasticity of hourly wages to a persistent (left panel) and transitory (right panel) productivity shock for workers within different age groups. Panel B shows the same statistics for workers within different tenure groups. Tenure is measured as the number of years for which the worker has been employed at that firm. Tenure bins are chosen so as to have groups of roughly similar size.

Third, consistent with the results shown in Figure 4, the effect on wages of a transitory shock to firms' productivity is weaker than the effect of a persistent shock (right plot of Panel A, Figure 5). In contrast to what we find for persistent shocks to productivity, however, we find that young workers gain more from a positive transitory shock and lose less after a negative shock than older workers. More precisely, for workers who are 25 years old or younger, a negative (positive) transitory shock of one standard deviation translates into a decrease (increase) of \$370 (\$251) in annual earnings. For workers who are 56 years old or older, a negative (positive) shock of the same magnitude generates a decrease (increase) of \$604 (\$184) in annual earnings.

We now turn to analyze the differences in passthrough across the workers' tenure distribution. To do so, we divide our sample of workers into five groups: workers with a tenure equal to 2 years or less, a tenure between 3 and 4 years, between 5 and 7 years, between 8 and 14 years, and 15 years or more.[33] Then, we run our baseline regression specification within each group. Importantly, as in our baseline estimates, we control for workers' age so that the following results reflect the effect on tenure that is independent of workers' age.

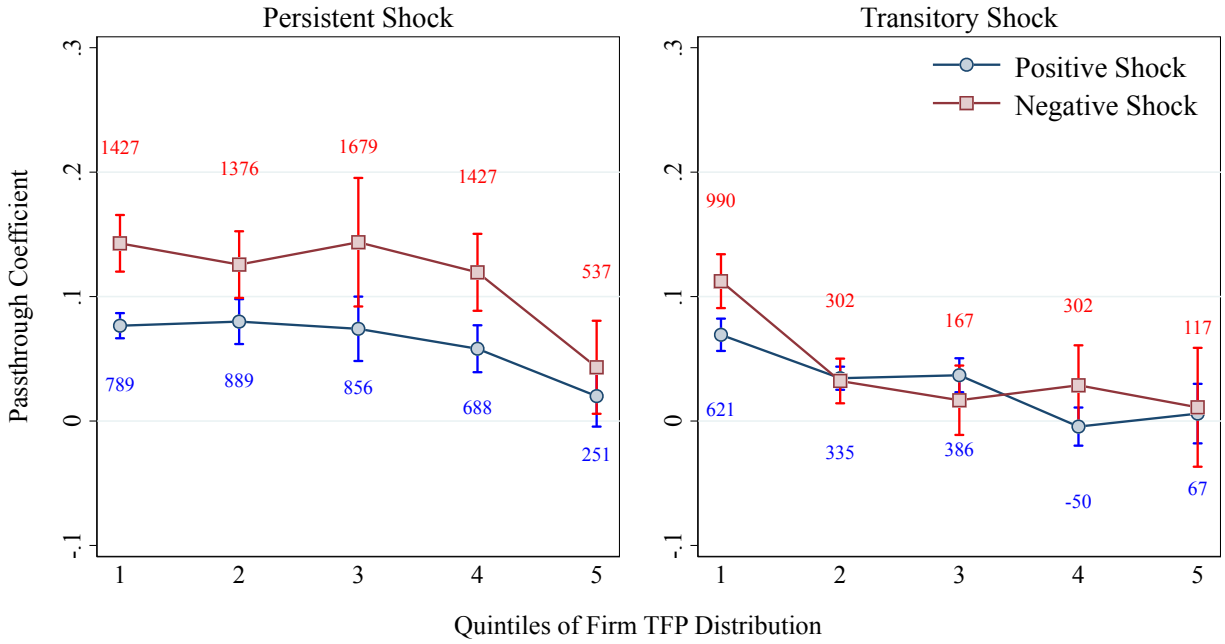
Panel B of Figure 5 summarizes our results. The left panel shows the elasticity of wages to a persistent shock to firms' idiosyncratic productivity for each tenure group. We find that the passthrough from persistent TFP shocks to wages is hump-shaped for negative shocks and increasing for positive shocks. In fact, the passthrough elasticity from negative shocks is almost the same for newly hired workers—those with a tenure of 2 years or less—as for workers who have been in the firm for more than 15 years. Workers in the middle of the tenure distribution, instead, appear to be much more exposed to negative firms shocks than the rest of the workers: when the shocks are negative, workers with medium tenure (between 5 and 7 years) lose the most, with a negative shock of one standard deviation generating a decline of \$2,115 (3.4%) in their annual average income.

As for transitory shocks, we find that passthrough increases significantly with tenure (right plot of Figure 5 Panel B): a negative transitory shock of one standard deviation generates a decrease in annual wages of \$201 for workers with less than 2 years of tenure, whereas for workers with 15 years or more of tenure, the decrease in wages after a shock of the same magnitude is \$688. In contrast, positive transitory shocks seem to drive a larger increase in wages for workers with less than 2 years of tenure than for those with 15 years or more.

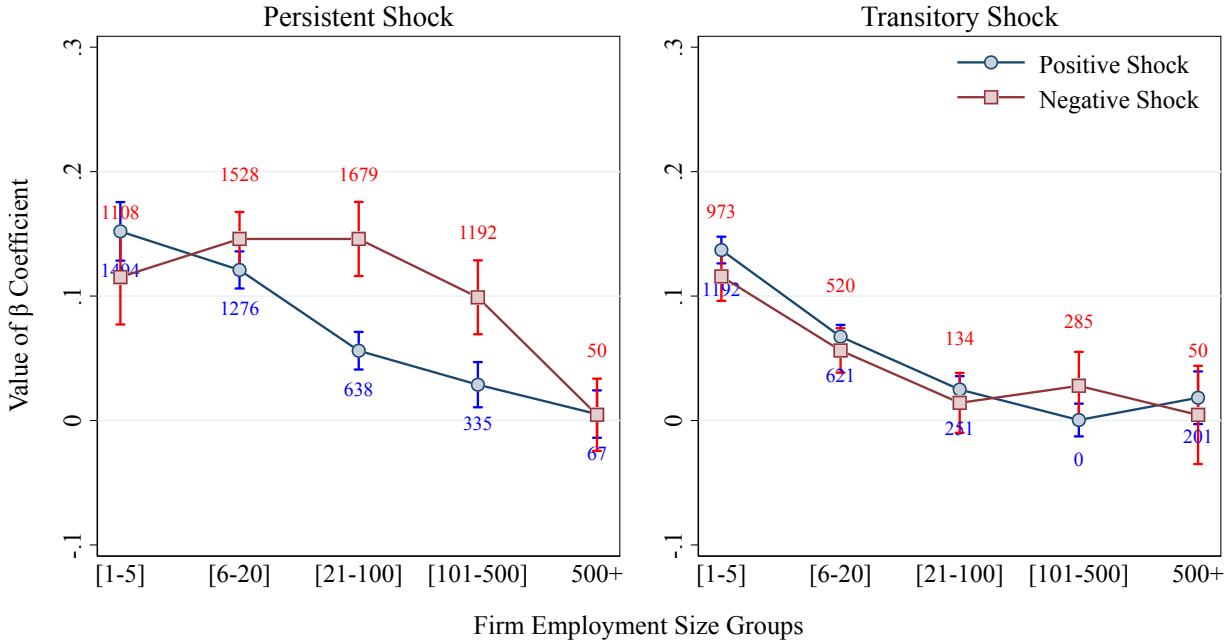
[33] We choose these tenure cutoffs so as to have groups of roughly similar size.

Figure 6 – Passthrough Across Firms' Characteristics

(a) Firm Productivity Level



(b) Firm Employment



Note: Panel A of Figure 6 shows the elasticity of hourly wages to a persistent (left panel) and transitory (right panel) productivity shock for workers employed by firms in different quintiles of the TFP distribution. Panel B shows the same statistics for workers employed in firms in different quintiles of the employment size distribution. In each plot, the points shows the passthrough elasticity coefficient (β) from a separate second-stage regression, while the vertical lines show 95% confidence intervals around those point estimates. In each plot, the numbers above and below the lines represent the monetary value of a shock of one standard deviation calculated using the corresponding elasticity. All monetary values (in 2010 US$) are calculated relative to the average annual labor earnings within the corresponding group.

6.2 Firm Heterogeneity

Firm Productivity

Firms with different productivity levels might also differ in the passthrough from shocks to wages. This would be the case if, for instance, firms have some degree of labor market power such that high productivity firms face an increasingly inelastic labor supply (as in the example in Section 5.1). As the labor supply curve becomes more inelastic, greater wage increases are required to obtain the same increase in labor, thereby increasing the measured passthrough. Alternatively, if larger or more productive firms have greater access to financial markets, one would expect the passthrough to decline with firm size and productivity, as highly productive firms can better insure themselves and their workers from productivity shocks, relative to low productivity firms.[34] Whether passthrough varies positively or negatively with firms' productivity is, however, a quantitative question, and our results are more consistent with this last interpretation. In fact, our estimates indicate that conditional on firm size, sector, and other firm- and worker-level characteristics, the wages of workers employed by low productivity firms are significantly more exposed to firm shocks than workers employed by high productivity firms, both for positive and negative shocks.

We show this by separating our sample of firms into quintiles by their (lagged) log TFP level, ν_{jt-1}, and running our baseline specification separately within each group. Panel A of Figure 6 shows our results. We find that passthrough from persistent shocks to firms (both negative and positive) is roughly decreasing in firms' productivity, especially in the top three quintiles of the distribution. For example, workers employed at firms in the lowest productivity quintile gain (lose) \$789 (\$1,427), or 1.5% (2.8%) in annual income on average when their firm experiences a positive (negative) persistent shock of one standard deviation. Workers employed at firms in the highest quintile of the TFP distribution, on the other hand, see much smaller wage changes. On average, these workers gain \$251, or 0.4% in annual income (lose \$537, or 0.8% in annual income) when their firm experiences a one standard deviation positive (negative) persistent shock.

The effect of transitory shocks—shown in the top right panel of Figure 6—is smaller, relative to the effect of persistent shocks, and also declines as one moves to the higher ranks of the log TFP

[34] Differences in passthrough across firm productivity levels might also help explain, for instance, the prevalence of a large-firm wage premium (Brown and Medoff, 1989) or the substantial dispersion of labor earnings observed across firms for workers with similar characteristics (Song *et al.*, 2019).

distribution, with firms in the top quintile having a passthrough for both positive and negative transitory shocks of roughly zero on average. Note that our finding that passthrough decreases with productivity is consistent with our evidence that passthrough is larger for negative shocks. If the passthrough elasticity is decreasing in productivity (as we find), then as noted above, discrete positive productivity shocks should have a smaller effect on wages (in percentage terms) than a discrete negative productivity shock.

Size and Market Power

Several firm characteristics besides productivity might impact the passthrough from firms' shocks to wages. The theoretical models described in Section 5 suggest that both absolute and relative firm size may play a role in determining passthrough. Hence, in this section, we discuss how passthrough varies along these dimensions. We find significant variation in passthrough across the total and relative firm size distributions.

We start by separating our sample of firms into groups by total employment (in full-time equivalents). We then run our baseline regression within each group. The results for transitory and persistent shocks are shown in Panel B of Figure 6. In general, we find that small and medium-size firms generate much larger passthrough than large firms. In fact, the passthrough elasticity for positive persistent shocks decreases monotonically with firm size. Passthrough from negative persistent shocks is also decreasing in size for firms with 21 or more workers (the top three size groups). Strikingly, the passthrough in firms with 500 or more employees is essentially equal to 0 for both positive and negative shocks. This indicates that very large firms are quite effective at insulating their workers from idiosyncratic firm-level risk. The smaller passthrough from large firms, relative to small firms, is also present for transitory shocks—see the bottom right plot of Figure 6.

It is possible that these size-conditional differences in passthrough reflect differences in the passthrough across industries or locations — perhaps manufacturing firms tend to be larger and also have less passthrough. We may also think that passthrough varies across firms within labor markets due to differences in labor market power. Firms with greater labor market power will tend to have larger labor market employment shares (conditional on productivity) and be situated on more inelastic portions of their labor supply curve. We investigate both of these issues by partitioning our firm sample into quintiles based on their employment share within a industry-

location bin.[35] By sorting firms in this way, we are able to look at the effect of relative size while controlling for differences in industry and location.

We show the results in Panel A of Figure 7. The results are similar to the total employment graph, but even more stark, with both positive and negative passthrough declining monotonically in labor market employment share for both persistent and transitory shocks. Workers employed in firms in the first quintile of the employment share distribution—i.e., small firms with around 0.6% employment in their local labor market—gain $1,026 from a one standard deviation increase in persistent productivity, and lose $2,082 from a negative shock of the same magnitude. In contrast, workers employed by firms in the fifth quintile of the employment share distribution—larger firms firms that account, in average, for by10% the employment of the local labor market—-are better insured, experiencing gains (losses) of $319 ($453) from positive (negative) persistent shocks of one standard deviation. This evidence seems to run contrary to the standard labor market monopsony model, where passthrough is increasing in size and labor market power.

Financial Constraints

We then study whether firms that are more financially constrained tend to have different passthrough rates than less financially constrained firms. Arguably, firms that are at or close to their borrowing constraint are less able to insure their workers after a negative productivity shock. To see whether this is the case, we follow Friedrich and Zator (2020), and we measure financial leverage for each firm in our sample as the ratio of total (long- and short-run) debt to total firm assets. We separate firms into quintiles of the financial leverage distribution and run our baseline regression within each group.[36] The results, shown in Panel B of Figure 7, indicate there is no monotonic relationship between passthrough and financial constraints. Instead, we find that firms in the middle quintile, with debt-to-asset ratios of roughly 0.7, have significantly less negative passthrough than both the high- and low-debt firms in the fifth and first quintiles of the leverage distribution, respectively. The passthrough from positive shocks does not seem to vary much across the leverage distribution.[37]

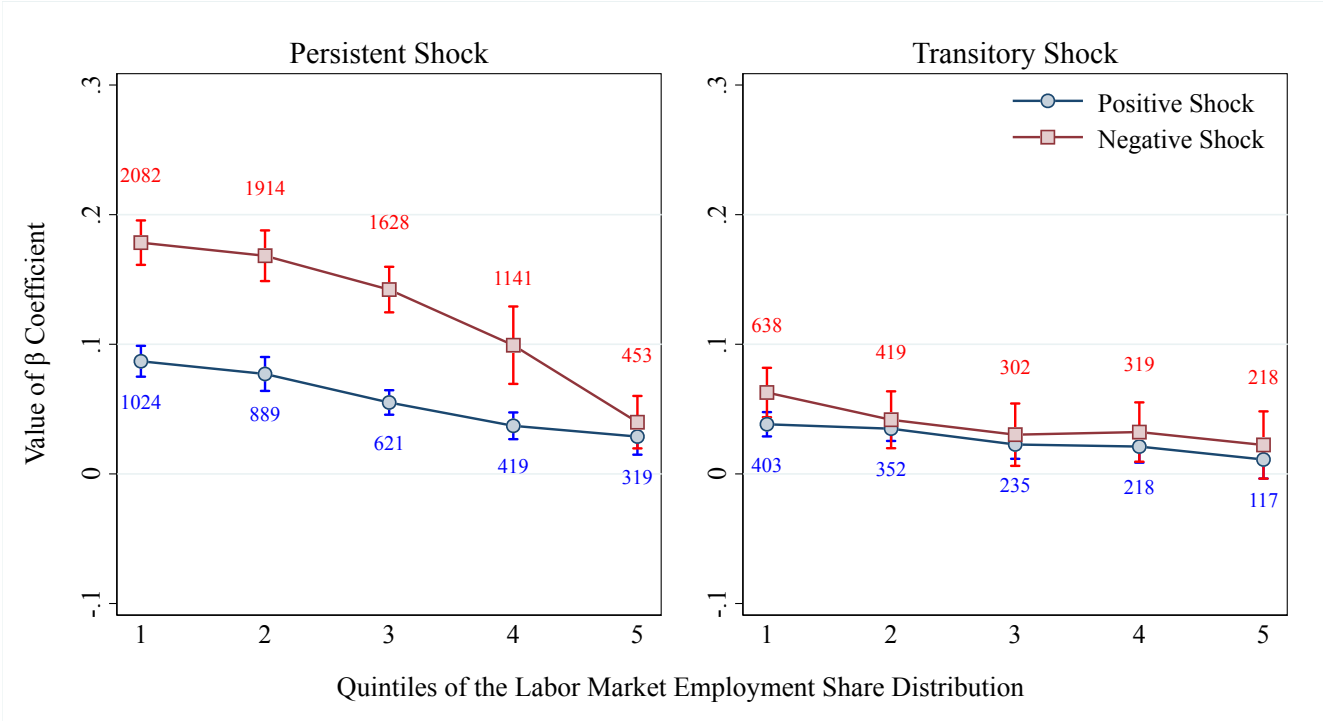
[35] We calculate employment shares within each industry-municipality, where an industry is defined at the 2-digit level. This is a fairly granular definition of a labor market, with the median firm within the top employment share quintile having a 10% share of employment within that market. To avoid the disclosure of any sensitive information, we calculate the median share within a quintile as the average share for all firms between the 50 and 51 percentiles of the employment share distribution within each quantile. Quintiles 1 through 4 have a within quintile median labor market shares of 0.6%, 1.4%, 4.7%, and 6%, respectively.

[36] The "median" debt-to-asset ratios for quintiles 1 through 5 are 0.37, 0.57, 0.69, 0.79, and 0.94, respectively.

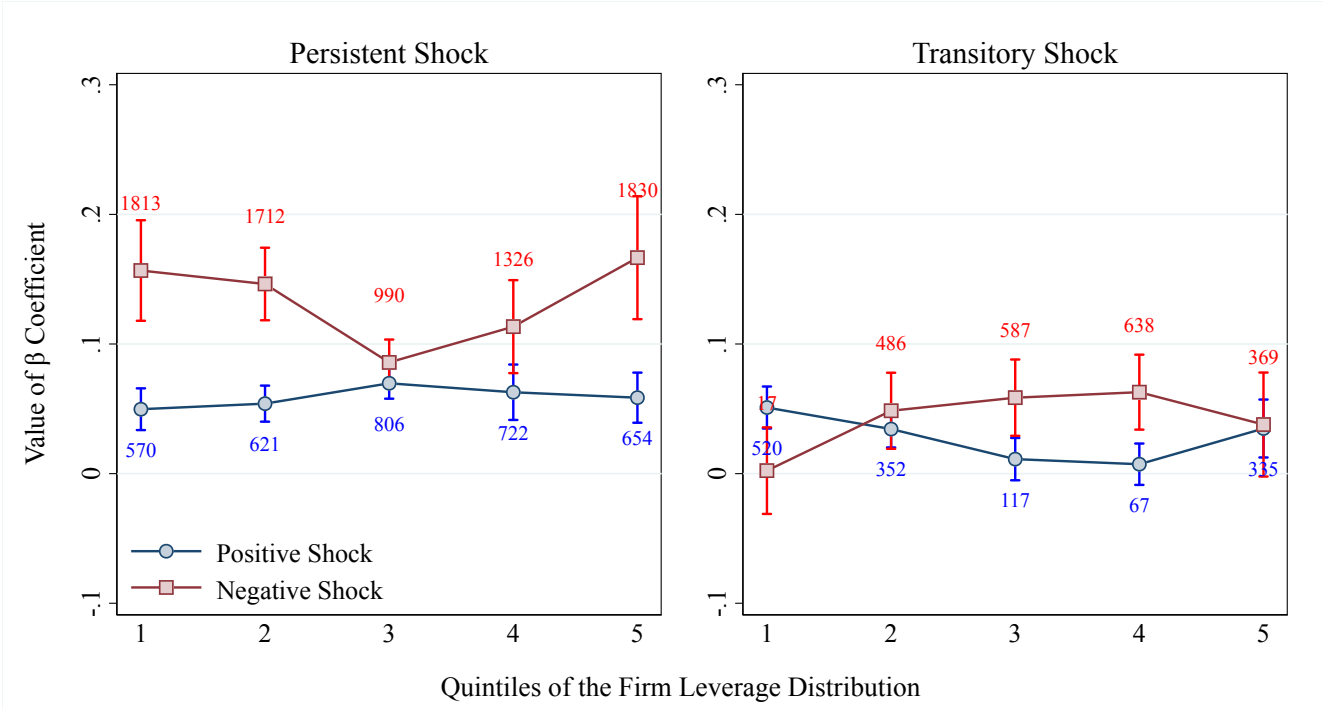
[37] We also check whether the passthrough varies across the firms' age distribution, which is another measure of financial constraint, but we do not find significant differences in the passthrough for younger versus older firms.

Figure 7 – Passthrough and Firms' Characteristics

(a) Labor Market Employment Share



(b) Financial Leverage



Note: Panel A of Figure 7 shows the elasticity of hourly wages to a persistent (left panel) and transitory (right panel) productivity shock for workers employed by firms in different quintiles of the labor market employment share distribution. Panel B shows the same statistics for workers employed in firms in different quintiles of the financial leverage distribution, defined as the total debt to asset ratio for the firm. In each plot, the points shows the passthrough elasticity coefficient (β) from a separate second-stage regression, while the vertical lines show 95% confidence intervals around those point estimates. In each plot, the numbers above and below the lines represent the monetary value of a shock of one standard deviation calculated using the corresponding elasticity. All monetary values (in 2010 US$) are calculated relative to the average annual labor earnings within the corresponding group.

6.3 State Dependance

Does the passthrough from idiosyncratic firms' shocks to workers' wages changes during recessions relative to expansions? This could be the case, if for example, a large aggregate economic shock, such as the Great Recession, decreases the workers' value of being unemployed (due to a reduction in vacancy postings).[38] This would lower workers' reservation wages and would possibly give firms greater ability to pass negative shocks on to their employees' wages. Similarly, if passthrough is linked to financial constraints, a large negative aggregate shock may tighten credit constraints, and thus reduce firms' ability to insure their workers against negative idiosyncratic productivity shocks, inducing a higher passthrough.

To investigate whether passthrough is state-dependent, we estimate Equation (8) for two different non-overlapping periods. The first period considers observations from the two years of the Great Recession (2008 and 2009), whereas the second period considers all of the other (expansion) years in our sample.[39] Our results, shown in columns (4) and (5) of Table VI, indicate that the passthrough from positive firm shocks to worker wages is state-dependent, whereas the passthrough from negative shocks is not, and remains the same between recession and expansion periods.

To see this, first notice that during expansion years, the passthrough coefficients are quite similar to those obtained in our baseline analysis—compare column (4) in Table VI to column (4) in Table V. This is not surprising, considering that most of the years in our analysis are expansionary years. Second, recession years show a different pattern, especially for the impact of persistent productivity shocks on wages. In particular, the passthrough from negative shocks remains almost unaltered between recessions and expansions (recall that the impact of a negative shock is given by $\beta_p^\eta + \beta_n^\eta$). In other words, firms that receive a negative idiosyncratic productive shock during a recession reduce the wages of their workers. In contrast, the passthrough from positive shocks collapses, becoming insignificant and almost zero, indicating that firms that received a positive productivity shock did not on average pass that increase on to their workers. The passthrough from transitory shocks, on the other hand, does not show significant variation over the business

[38] Similar to the rest of the world, Denmark was hit by a severe economic downturn in 2008. The decline in the Danish GDP was underway at the beginning of 2008 and was accompanied by a large increase in unemployment. Between 2007 and 2009, the GDP of Denmark declined around 7.0%, while the unemployment rate increased by 2.0 percentage points. In response, the Danish government increased the expenditure per unemployed worker more than any other country in the OECD (Schmitt, 2015).

[39] In order to have a clearer comparison, we exclude the years 2002 and 2003 during which Denmark experienced a mild recession.

cycle.

In conclusion, our results suggest that recessions are neither periods in which firms are unable to cut wages when facing an idiosyncratic negative shock, nor periods with a higher passthrough from negative shocks. Rather, firms do not increase workers' wages when facing a positive idiosyncratic shock.[40] Hence, although wages during recessions may appear to be less flexible than during expansions, this is not because firms cannot decrease wages—as would be the case, for instance, if there were a union keeping workers' wages up or because the firms' managers were worried about maintaining workers' effort.

7 Switchers

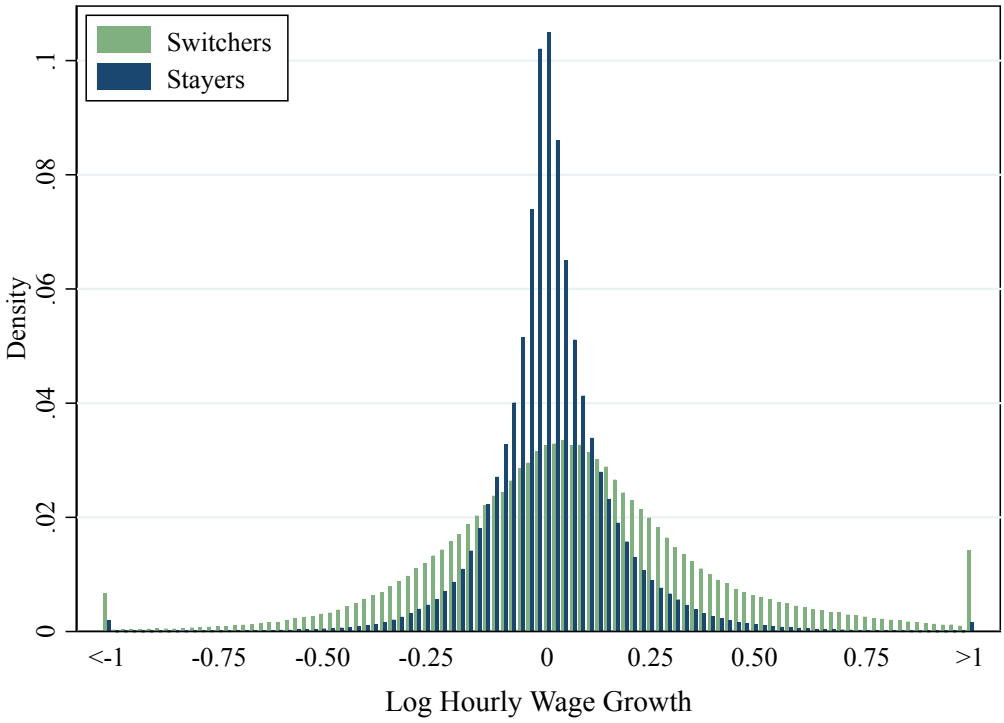
The results of the previous sections have focused on the effect of TFP shocks on stayers, that is, workers who maintain a stable employment relationship with a firm for the years over which the change in TFP is calculated. This is a natural starting point, as changes in wages for incumbents workers can be easily tied to changes in firm productivity. In this section, we shift our focus to individuals who change employers. There are at least three reasons why one should also study the impact of firms' productivity shocks on these workers. First, employment risk is an important source of labor income fluctuations for workers, which might be partially driven by firms' idiosyncratic shocks. Second, a large group of workers switch employers every year: in our sample, around 20% of workers change employers in any given year. Third, standard job ladders models (Burdett and Mortensen, 1998) predict that workers transition from low to high productivity firms over time; hence, workers are likely to move from firms whose productivity is declining to firms whose productivity is increasing.

Our data allows us to directly look at the change in wages of workers moving between low and high productivity firms and between firms receiving negative and positive productivity shocks. We define switchers as those workers who change primary employers between two consecutive years.[41] Figure 8 shows the distribution of the (residual) log hourly wage growth for our sample of job-switchers (green bars), relative to the distribution of hourly wage growth for stayers (blue bars).

[40] Our results are consistent with those presented by Grigsby *et al.* (2019) that show that during the Great Recession, the probability of US workers of receiving a (nominal) wage cut increased whereas the probability of receiving a wage increase fell sharply.

[41] For workers with multiple jobs in a year, we define the primary employer as the firm that provides the higher income within a year. Our data does not allow us to cleanly distinguish whether an individual passed through an unemployment spell prior to joining a different employer or had a direct transition between employers.

Figure 8 – Log Hourly Wage Growth For Switchers and Stayers

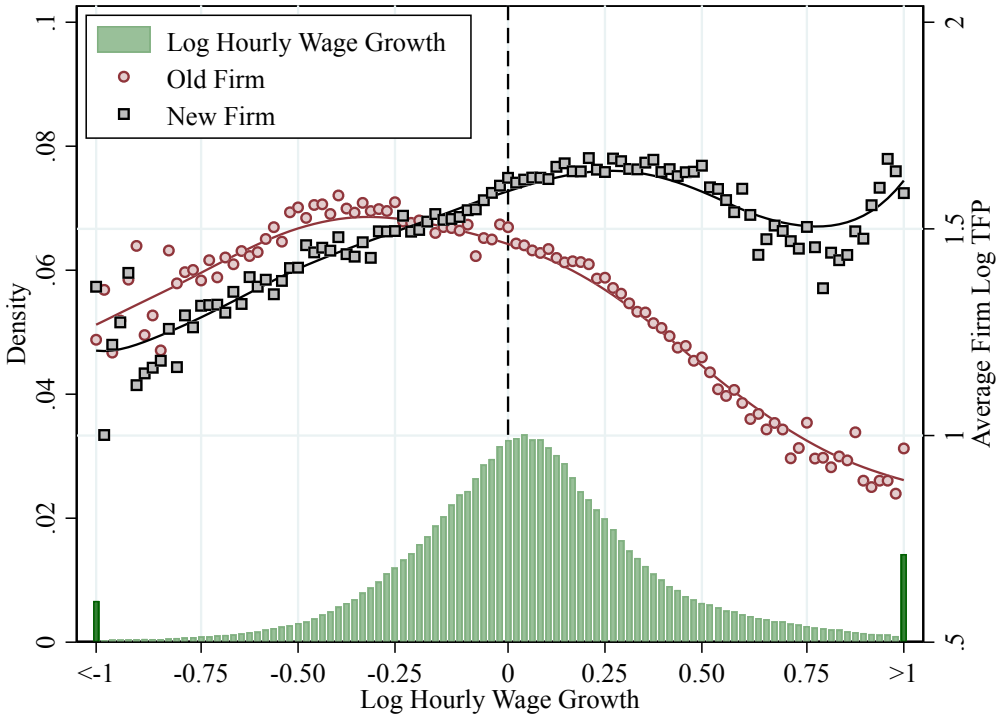


Note: Figure 8 is based on a pooled sample of stayers and switchers (workers who move across firms between firms $t-1$ and t) and their corresponding firms. In the top panel, the green bars (blue bars) show the share of switchers (stayers) within different bins of the hourly wage growth distribution (left y-axis). To construct the graph we partition the wage growth distribution into 101 equally-spaced bins between -1 and 1. The left- and right-most bins encompass the remaining left and right tails of the distribution, and thus are not the same size as the other bins.

The dispersion of the hourly wage growth for switchers is much higher, with a larger fraction of workers in the tails of the distribution.

The large wage growth dispersion for switchers relative to stayers is explained, in part, by the fact that switchers are transitioning between firms of (often significantly) different productivity levels. This is shown in Figure 9, where we plot (on the right y axis) the average log TFP of the two firms between which workers are transitioning within bins of the wage growth distribution (x axis). Each red circle in Figure 9 is the average log TFP of the firms *out of which* workers of a given wage growth percentile switched, while each black square is the average log TFP of the destination firms *into which* workers of the corresponding wage growth percentile switched. Two patterns are worth noticing. First, the difference in firm productivity between positive and negative wage changes is striking. Workers who receive a reduction in hourly wages of between 25 and 75 log points at their new firm, relative to their old firm, move on average to firms that are 10 log points less productive. In contrast, workers who experience an increase in hourly wages of 25 log points move to a firm that is on average 26 log points more productive. Moreover, the

Figure 9 – Log Hourly Wage Growth For Switchers and Firm TFP



Note: Figure 9 is based on a pooled sample switchers (workers who move across firms between firms $t-1$ and t) and their corresponding firms. The green bars show the share of switchers within different bins of the hourly wage growth distribution (left y-axis). To construct the graph we partition the wage growth distribution into 101 equally-spaced bins between -1 and 1. The left- and right-most bins encompass the remaining left and right tails of the distribution, and thus are not the same size as the other bins. The red dots show the average log TFP of the firms that employed the workers in the corresponding wage change bin in period $t-1$. The black squares show the average TFP for the firms that employed the workers in each bin in period t.

difference in productivity increases as workers experience larger wage gains. For example, workers who gain between 50 and 75 log points in wages have moved on average to firms with around 50 log points greater productivity than their old firm. There is also a group of workers who, despite experiencing a wage cut of between 0 to 20 log points, have moved to firms with greater average productivity, perhaps motivated by prospects of higher future wage growth.[42]

A second noticeable pattern of Figure 9 is that workers receiving larger year-to-year wage gains from switching firms are not moving, on average, to firms with higher productivity, relative to workers with smaller, but still positive, wage gains. Instead, workers with larger wage gains tend to be those switching out of relatively lower productivity firms. Workers whose log hourly wages increase by 50 log points are switching on average into firms with the same productivity as workers who gain 10 log points in hourly wages, but are switching out of firms that are 25 log points less

[42]We find similar patterns when looking at different percentiles of the distribution of the log TFP (Figure A.4 in Appendix A). In particular, the higher average productivity of switchers' new firms is not driven by a handful of highly productive firms that are offering higher wages, but rather the entire distribution of destination firms is shifted to the right

Figure 10 – Log Hourly Wage Growth for Switchers and Log TFP Growth

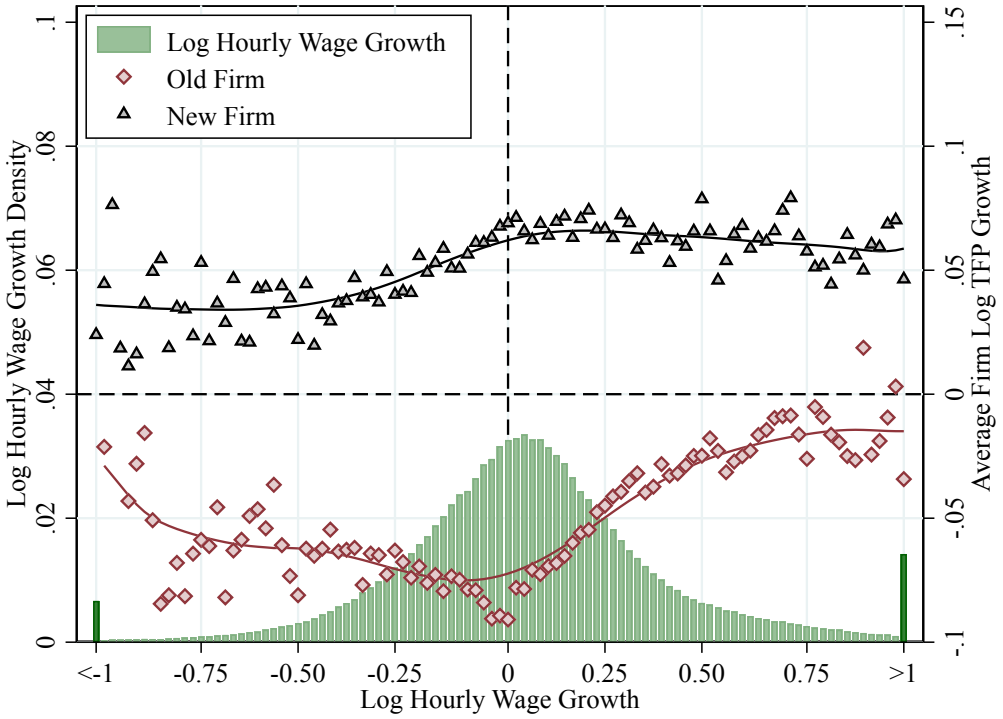


Figure 10 is based on a pooled sample of switchers (workers who move across firms between firms $t-1$ and t) and their corresponding firms. The green bars show the share of workers within different bins of the hourly wage growth distribution (left y-axis). To construct the graph we partition the wage growth distribution into 101 separate bins between -1 and 1. The left and right-most bins, marked in darker green, encompass the remaining left- and right tails of the distribution, and thus are not the same size as the other bins. The red diamonds (black triangles) shows the average log TFP growth of the old old (new) firm that employed the worker.

productive.

Interestingly, workers move in average to firms with positive TFP *growth,* independently of whether the hourly wage growth is positive or negative. This is shown in Figure 10 that displays, in the right y-axis, the average TFP growth for the new and old firms for switchers within bins of the wage growth distribution (plotted x-axis). Notably, the average switcher in every bin of the wage growth distribution is moving from a firm with negative productivity growth and into a firm with positive productivity growth. This indicates that expanding firms (those with positive productivity growth) capture workers from other firms, even from those firms with higher—but declining—average productivity.

These findings are consistent with the results obtained from the selection model of Section 3.3, where we find that the probability that a worker leaves their firm depends on the magnitude and sign of the productivity shock experienced by their firm. In fact, we find large variation in the probability that a worker switches firms across the firm TFP growth distribution. To show this, we use a linear probability model similar to Equation 5 to calculate the probability of switching,

Figure 11 – Conditional Probability of Switching

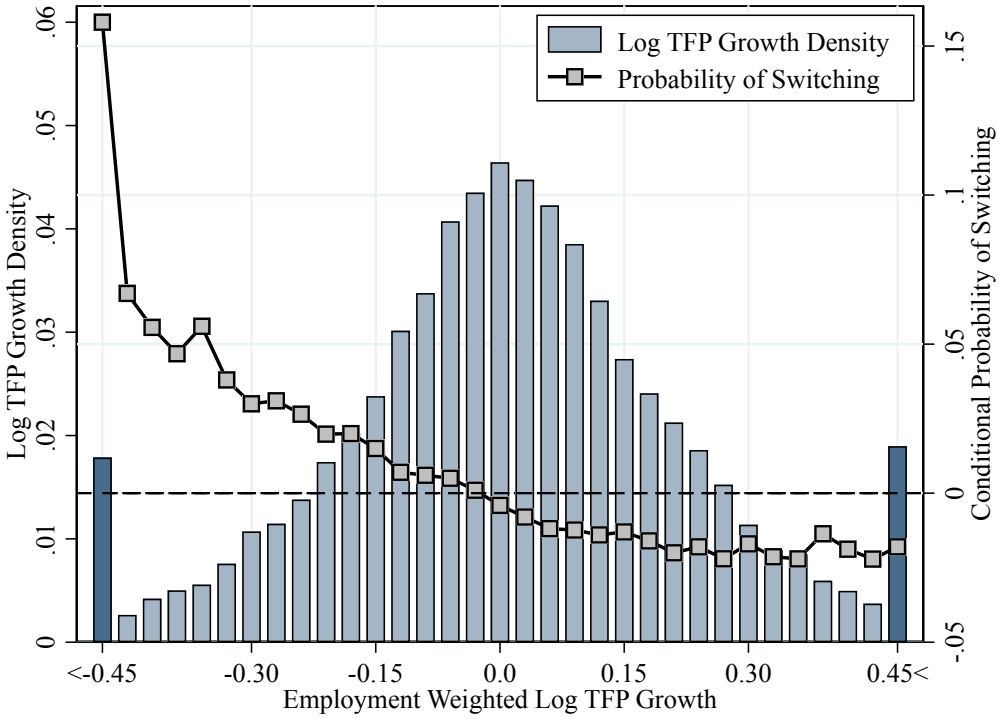


Figure 11 shows the average conditional switching probability within each bin of the firms' log TFP grow distribution ($\Delta\nu_{jt}$). The conditional probability is obtained from a linear probability model similar to the model used to estimate the inverse Mills ratio. See Section (3.3) for additional details.

conditional on worker and firm characteristics. Figure 11 displays the conditional probability within bins of the TFP growth distribution. As implied by the results of the first-stage probit regressions of Equation 5 in Table III, changes in firm TFP are a significant driver of worker mobility. For instance, workers employed in firms that experience a negative change in productivity of 30 log points have a 4% probability of switching, whereas workers employees in firms that experience a decline in productivity of 45 log points or more, have a 15% probability of switching firms in the following period. In contrast, the conditional probability of switching firms is negative for workers employed at firms that receive a positive productivity shock implying that workers employed in this firms have a lower-than-average provability of moving to a different firm in the next period.

Regression Results

To obtain quantitative estimates of the between-firm passthrough elasticity, we run a set of panel regressions similar to the baseline model we consider in our stayers sample. Notice that for switchers, however, the interpretation of a productivity shock is different than for stayers. For stayers, it represents an *unanticipated* change in productivity in the firm in which they work, whereas for switchers, we define a TFP shock here as the *unanticipated* difference in productivity

between two different firms. Hence, a positive TFP change for a switcher implies that the worker moved to a firm with higher realized, TFP relative to the *expected* TFP of the firm at which the worker used to work. These transitions may have been motivated by a productivity decline in the firm of origin, an increase in the productivity of the new firm that poached the worker, or both.

To capture these differences, we modify our baseline specification to include the shocks to the productivity of both of the firms between the individual is transitioning. In particular, we estimate

$$\begin{aligned}\Delta\hat{w}_{ijkt} = \; & \alpha + \beta_p^{\eta}\eta_{jkt} + \beta_n^{\eta}\eta_{jkt} \times \mathbb{I}_{\eta_{jkt}<0} + \beta_p^{\varepsilon}\varepsilon_{jkt} + \beta_n^{\varepsilon}\varepsilon_{jkt} \times \mathbb{I}_{\varepsilon_{jkt}<0} \\ & + Z_{jt}\Gamma_1 + Z_{kt}\Gamma_2 + X_{it}\Lambda + \rho\tilde{\lambda}_{ijt} + \delta_t + \zeta_{ijkt},\end{aligned}$$

where $\Delta\hat{w}_{ijkt}$ is the change in the real log hourly wages of an individual who works in firm j and who moved from firm k. Notice in this case that η_{jkt} is defined as the unanticipated change in the persistent component of TFP between the old and new firms, given by $\eta_{jkt} = \omega_{jt} - \mathbb{E}[\omega_{kt}|\omega_{kt-1}]$, whereas ε_{jkt} is simply the transitory shock at the new firm. The matrices Z'_{jt} and Z'_{kt} include firm $j's$ and $k's$ characteristics such as size, age, and lag productivity. As before, the main coefficients of interest are β_p^{η}, which captures the elasticity of wages in response to a persistent positive TFP shock, and β_p^{ε}, which captures the elasticity of a change in wages in response to a positive transitory TFP shock. The elasticity with respect to a negative persistent shock is then $\beta_p^{\eta} + \beta_n^{\eta}$ and for a negative transitory shock is $\beta_p^{\varepsilon} + \beta_n^{\varepsilon}$.[43]

Column (3) of Table VI shows the results of this analysis. Notice that the elasticity of switchers' wages to firms' TFP shocks is smaller than for stayers (compare to column (4) in Table V), but the dollar value of the shock is much larger for switchers (bottom panel of Table VI). The large difference in the dollar values between switchers and stayers stems from the differences in the dispersion of TFP changes, as well as differences in the average wage. For example, the elasticity of wage growth to a persistent shocks to TFP is much larger for stayers than for switchers when the shock is negative (0.131 versus 0.027). However, the average wage loss from a one standard deviation within-firm negative TFP shock for stayers is smaller than the loss for switchers who experience a persistent one standard deviation firm-to-firm drop in TFP (compare \$1,495 versus \$1,914, or 2.5% versus 3.4% of annual average income).

[43] We control for selection in this regression by including the inverse Mills ratio $\tilde{\lambda}_{ijt}$ which is estimated from a first-stage model similar to Equation 5, with the exception that D_{ijt} is instead an indicator that equals 1 if the worker moved to a different firm in period t.

Switchers also experience much larger wage increases than stayers after a positive productivity shock: a one standard deviation increase in firm-to-firm productivity is associated with a \$2,099 gain in annual wages for switchers, compared to a \$688 gain for stayers who experience an increase in productivity of the same (relative) magnitude. These results reflect the notion that workers often move up or down in the wage ladder when they decide to switch jobs, as is evident from Figure 9. One additional remarkable difference with respect to stayers is that the passthrough for switchers is *symmetric* (the coefficient of $\eta_{jt} \times \mathbb{I}_{\eta_{jt}<0}$ is basically 0 in column (3) of Table VI). That implies that workers climbing up or down the productivity ladder gain and lose equally regardless of the shift in relative productivity. This suggests that the within-firm passthrough asymmetry is driven by interactions between the firm and the workers themselves, rather than anything inherent in the wage or productivity differences.

8 Implications for the Labor Supply Elasticity

Our estimates of the passthrough elasticity can also give us intuition about the underlying labor supply curve. As shown in section 5.1, a simple decomposition of the passthrough elasticity shows that it will be inversely related to the elasticity of labor with respect to wages. Rearranging Equation 10 the following relationship between the labor supply elasticity and the elasticities of wages and labor with respect to productivity: $\varepsilon_w^L = \varepsilon_A^L / \varepsilon_A^w$. As mentioned above, a standard modeling assumption has been that labor markets are perfectly competitive, implying an infinite labor supply elasticity and a passthrough elasticity of zero. More recently, a growing literature has attempted to obtain empirical estimates of these labor supply elasticities, often finding very low elasticities (see Manning (2011)and Card *et al.* (2018)). For example, Dube *et al.* (2020) attempt to measure the elasticity directly using data from Mechanical Turk and find an implied elasticity of around 0.1. Azar *et al.* (2019) use application data from CareerBuilder.com to estimate a model of demand for job vacancies and recover (somewhat more reasonable) labor supply elasticities of around 5.

The main difficulty in identifying the elasticity is finding exogenous variation in wages. While estimating the labor supply elasticity is not the primary purpose of this paper, our framework and data do provide several advantages we can leverage. In particular, given our exogenous measures of firm productivity, it is straightforward to extend our data and method to obtain estimates of the elasticity of labor with respect to productivity, which we can then use along with the passthrough

Table VII – Elasticity of Labor with respect to Productivity

	(1) Δa_{jt}	(2) Δa_{jt}
β_a^ν	$.72^{***}$	$.43^{***}$
	(.032)	(.027)
Controls	No	Yes
R^2	.30	.76
Obs. (Millions)	.47	.47
Labor Supply Elasticity	9.47	5.66

Table VII shows two OLS panel regressions with and without controlling for firm characteristics. a_{jt} is log total ability-adjusted labor. ν_{jt} is the log of total firm TFP. Firm controls include lags of firm age, TFP, ability-price (wage), and employment. $*p < 0.1, **p < 0.05, ***p < 0.01$. We report the robust standard errors in parentheses. The implied labor supply elasticity is calculated by dividing β_a^ν by the passthrough elasticity estimate from column 1 of Table V (0.076).

elasticity estimates to back out the labor supply elasticity. To do this, we estimate the following regression model at the firm level,

$$\Delta a_{jt} = \alpha + \beta_a^\nu \Delta \nu_{jt} + Z_{jt}\Gamma + \delta_t + \zeta_{jt}^f$$

where $a_{jt} = \log A_{jt}$ is the log of the firm's total ability-adjusted labor input, ν_{jt} is log TFP, and Z_{jt} is a vector of firm characteristics including the firm-level ability price (wage). We weight this firm-level regression by (lagged) total ability-adjusted employment so that it corresponds to our individual-level estimates of Equation 6. Our parameter of interest is β_a^ν which will give us an estimate of the elasticity of labor with respect to productivity, ε_A^L. The results are displayed in Table VII.

The second column shows our estimate for ε_A^L once we control for firm wage and other firm characteristics. The very precise estimate of 0.43 means that a 1% increase in productivity on average leads to a 0.43% increase in (ability-adjusted) labor. We can combine this with our baseline passthrough elasticity estimate from Table V, which was 0.076. Together, these results provide us with an implied labor supply elasticity of $0.43/0.076 = 5.66$, which is very similar to the results obtained by Azar *et al.* (2019) despite using very different methods and data. A labor supply elasticity of 5.66 suggests (through the lens of our simple monopsony model) an average

wage markdown of 15%, which means that firms do seem to have substantial labor market power.

9 Conclusions

In this paper, we present new evidence on the passthrough from firms' productivity shocks on workers' wages. We show that the passthrough elasticity—defined as the percentage variation in hourly wages generated by a percentage change in firms' productivity—is not only economically and statistically significant, but also markedly asymmetric, in that a negative shock to firm productivity generates a much larger decline in wages, relative to the gain in wages from a positive shock to firm productivity of the same magnitude.

Our results are based on high-quality employer-employee matched administrative panel data from Denmark that we use to address two important issues that have been overlooked by the empirical literature: the effect of selection and the impact of changes in firm-level productivity for workers who switch between firms. To accomplish this, we provide a more direct measure of firms' total factor productivity that is arguably exogenous to variation in inputs (such as capital and material) and controls for differences in labor quality across firms . To control for selection, we use a novel approach that exploits the employment and income information of workers' spouses to estimate the probability that an individual stays in the same firm during a particular year. We find that controlling for selection has a significant impact on the estimated passthrough from firms' TFP shocks to workers' wages.

Quantitatively, we find that the passthrough from firms' TFP shocks to workers' wages is statistically and economically significant: controlling for selection, we find that workers employed in a firm that experiences an increase in TFP one standard deviation see their annual earnings increase by $1,100, which is around 2% of the average Danish annual labor income. Most of this effect is driven by persistent shocks to firms' productivity. We also find substantial variation across several key dimensions of worker and firm heterogeneity which give us insights into which theoretical mechanisms are more likely to be driving the observed passthrough from productivity to wages. On the worker side, we find that high-income and younger workers are more exposed to firms shocks, especially if these shocks are negative. On the firm size, we find that large and more productive firms have significantly lower passthrough than small and less productive firms. Taken together, our results suggest an important role for firms' productivity in determining workers' wages.

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Appendix

A Additional Tables and Figures

Figure A.1 – Passthrough from Firms' Persistent Productivity Shocks to Wages

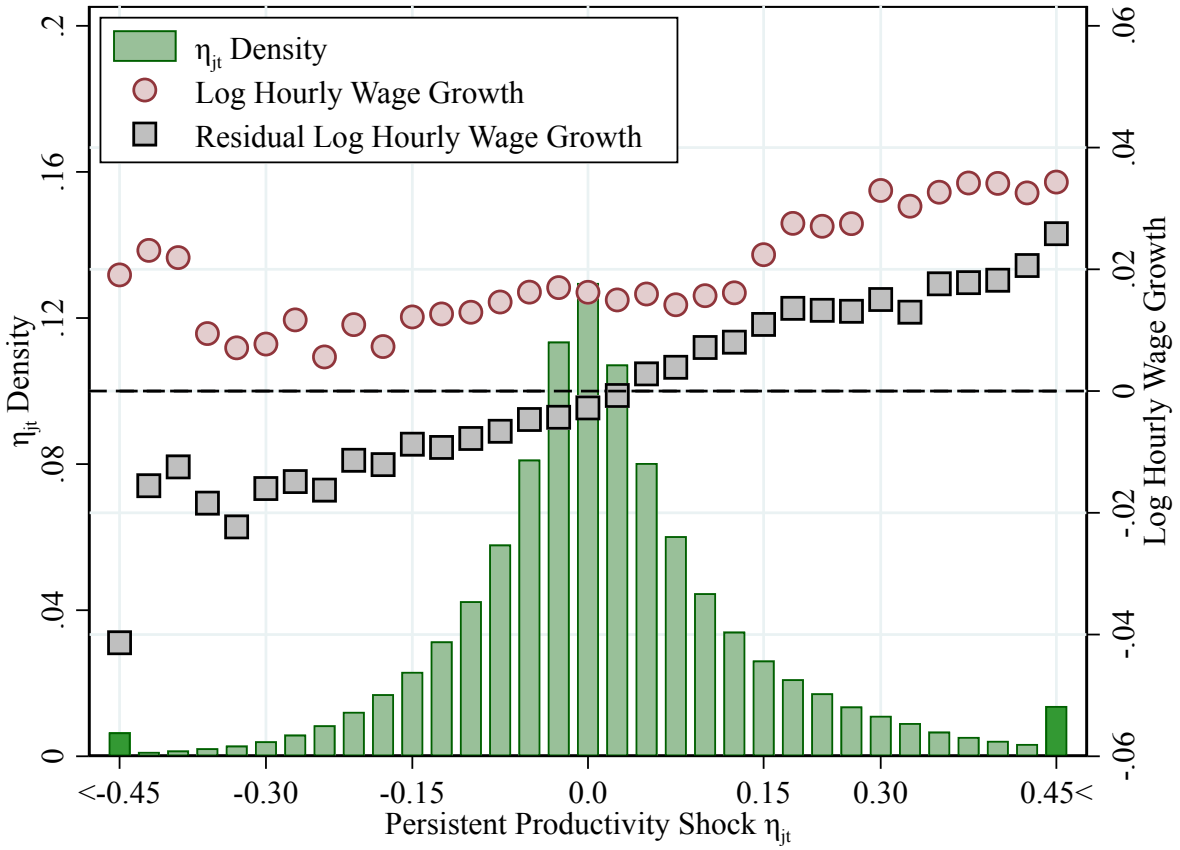
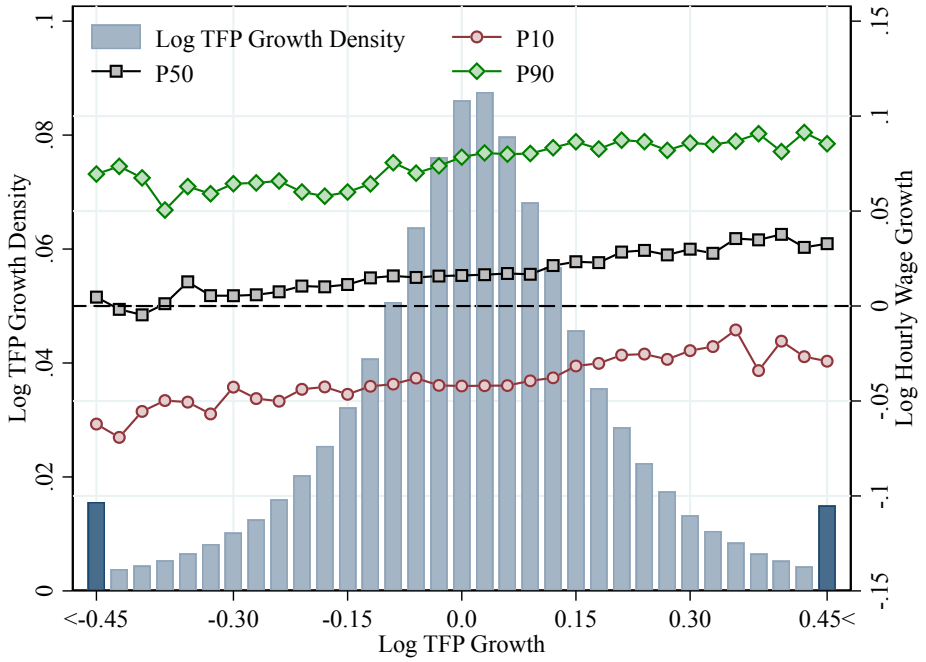


Figure A.1 is based on a pooled sample of firms and workers between the years 1996 to 2010. The blue bars show the share of firms within different bins of the persistent shock (η_{jt}) distribution (plotted on the left y-axis). To construct the plot, we separate firms into 41 equally spaced bins between -.45 and 45. The left- and right-most bins, marked in darker green, encompass the remaining left and right tails of the distribution, and thus are not the same size as the other bins. The red circles show the average log hourly wage growth for all workers employed by firms within a bin (plotted on the right y-axis). The black squares show the average hourly wage growth after controlling for worker characteristics, firms characteristics, and endogenous selection as explained in Section 3.3 (plotted on the right y-axis). Hourly wage growth and residual hourly wage growth are calculated for a sample of stayers defined as workers for whom the firm providing the higher total annual earnings was the same in periods t and $t-1$.

Figure A.2 – Wage Change Percentiles Across the TFP Change Distribution

(a) Hourly Wages



(b) Adjusted Hourly Wages

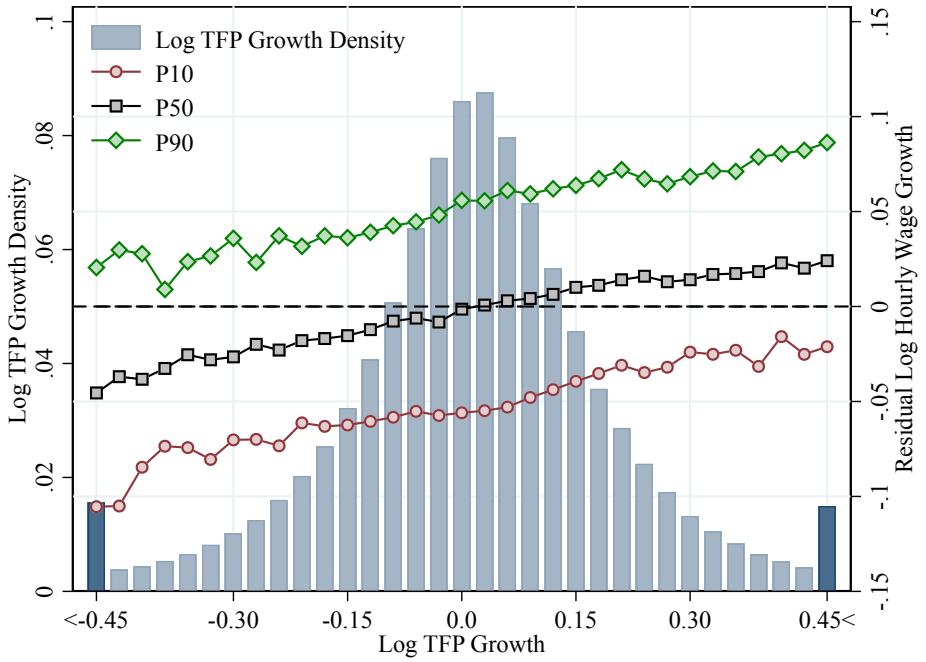
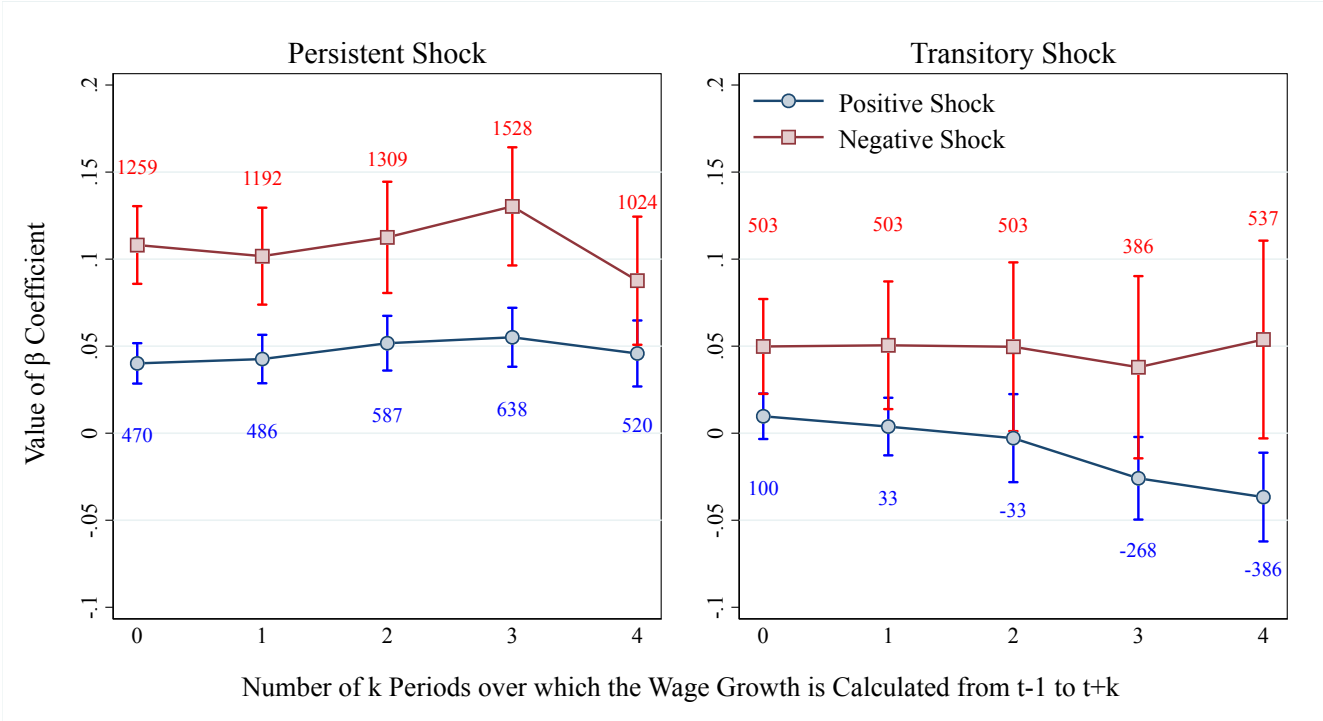


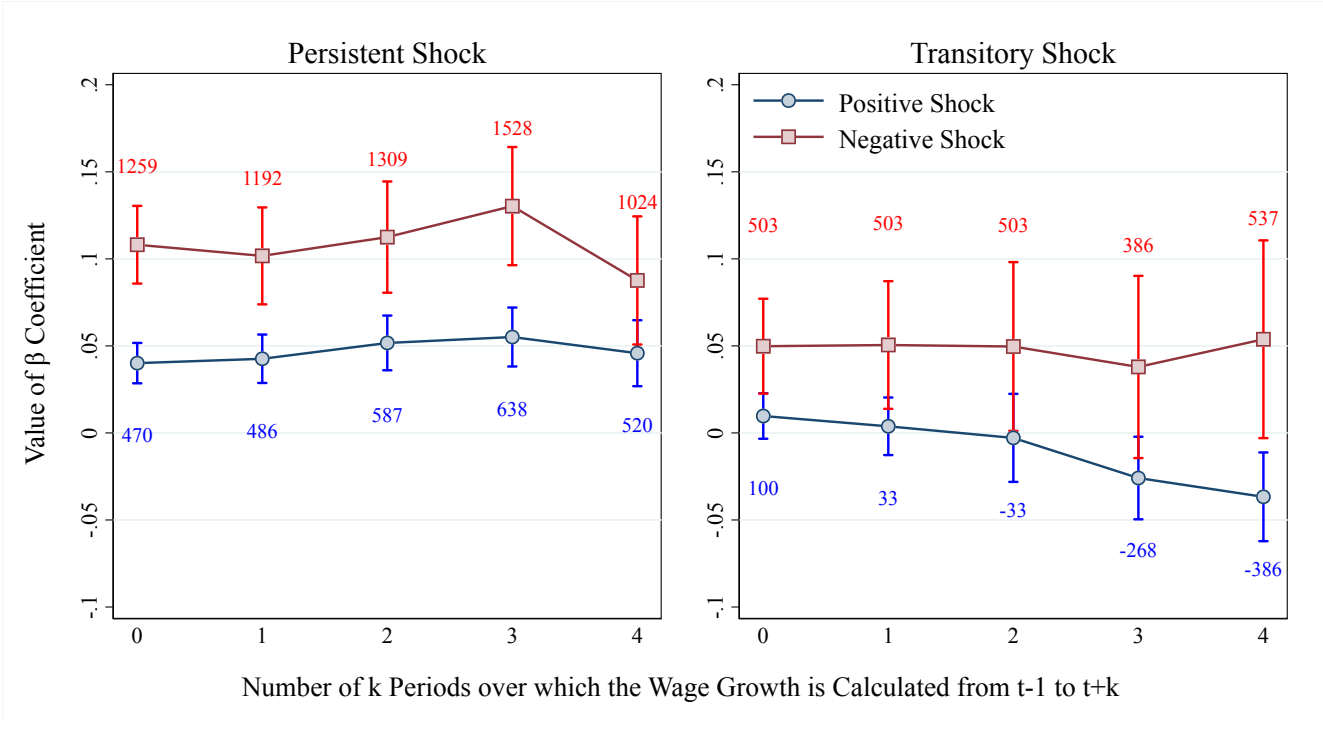
Figure A.2 is based on a pooled sample of firms and workers between the years 1996 to 2010. The blue bars show the share of firms within different bins of the log TFP growth distribution (plotted on the left y-axis). To construct the plot we separate firms into 41 equally sized bins between -.45 and 45. The left- and right-most bins, marked in darker blue, contain the remaining left and right tails of the distribution, and thus are not the same size as the other bins. The right axis of each panel shows the within-percentiles means of the hourly wage growth (top panel) and hourly wage growth after controlling for worker characteristics, firm characteristics, and endogenous selection as explained in Section 3.3 (bottom panel). Hourly wage growth measures are calculated for a sample of stayers defined as workers for whom the firm providing the higher total annual earnings was the same in periods t and $t-1$. To avoid disclosure of any sensitive information, we report the mean of all observations *within* a percentile-band rather than individual observations at the percentile cutoff.

Figure A.3 – Positive and Negative Shocks Have a Long-Lived Impact on Wages

(a) Positive and Negative Shocks



(b) Positive and Negative shocks for a Balanced Panel of Workers



Note: Figure A.3 shows the elasticity of hourly wages to firm productivity. In each plot, hourly wage growth is measured as the change between year t and $t+k$ where k is plotted on the x-axis. Firms' productivity shocks are measured by η_{jt} (left panel) and ϵ_{jt} (right panel). In each plot, the points shows the passthrough elasticity coefficient (β) from a separate second-stage regression, while the vertical lines show 95% confidence intervals around those point estimates. In each plot, the numbers above and below the lines represent the monetary value of a shock of one standard deviation calculated using the corresponding elasticity. All monetary values (in 2010 US$) are calculated relative to the average annual labor earnings within the corresponding group.

Figure A.4 – Hourly Wage Growth for Switchers and Firm Productivity

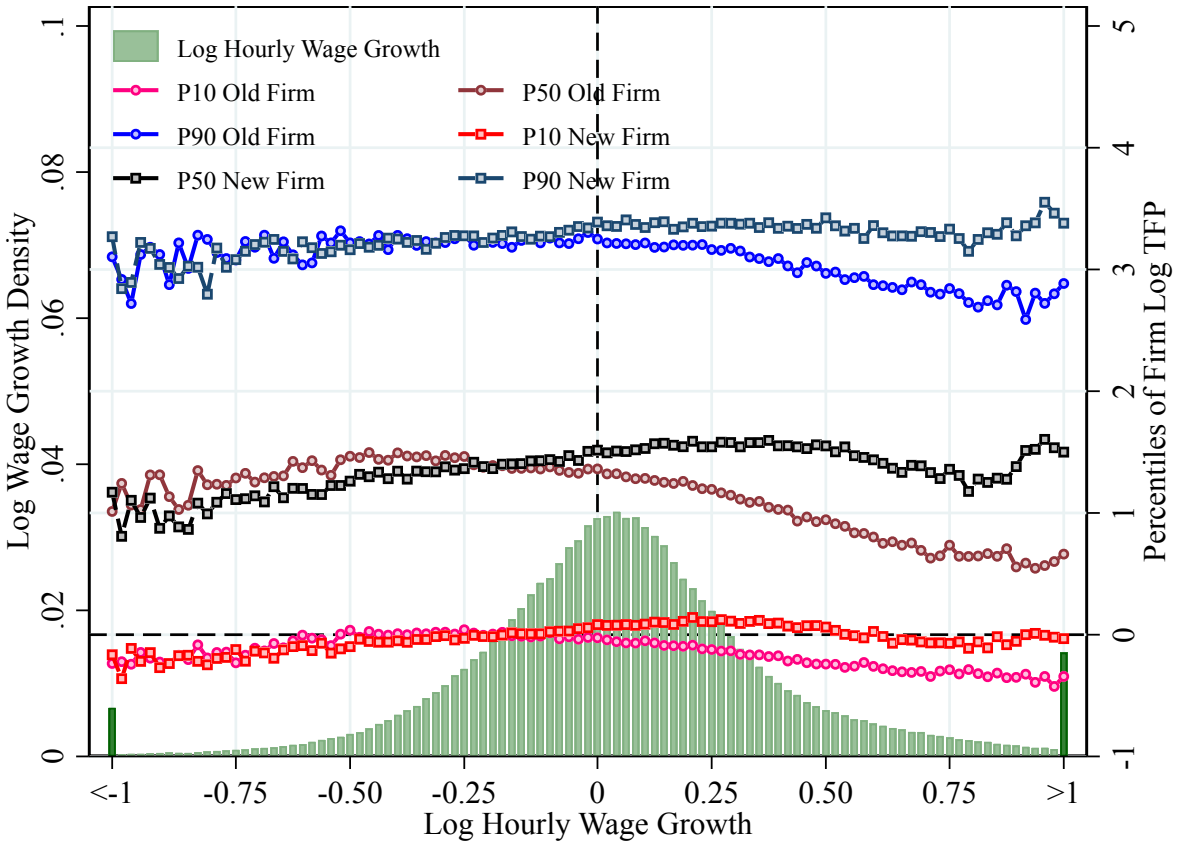


Figure A.4 is based on a pooled sample of switchers (workers who move across firms between firms $t-1$ and t) and their corresponding firms. The green bars show the share of workers within different bins of the hourly wage growth distribution (left y-axis). To construct the graph we partition the wage growth distribution into 101 equally spaced bins between -1 and 1. The left and right-most bins, marked in darker green, encompass the remaining left and right tails of the distribution, and thus are not the same size as the other bins. The circles show percentiles of the log TFP distribution for the firms that employed the workers in period $t-1$; The squares show percentiles of the log TFP distribution for the firms that employed the workers in period t. To avoid disclosure of any sensitive information, we report the mean of all observations *within* a percentile-band rather than individual observations at the percentile cutoff.

B Identification in an AKM Framework with Time Varying Fixed Effects

In this appendix we discuss identification of the parameters in our model of wages with two sided fixed effects and time-varying firm characteristics. Recall the model of wages we use is given by:

$$w_{ijt} = \alpha_i + X_{it}\Gamma_t + \psi_{j(i,t)t} + \xi_{ijt},$$

Heuristically, identification can be shown in three parts: the time-varying covariate coefficients, the individual fixed effects. and the time-varying firm fixed effects.

First, we discuss the identification of the coefficients on the individual covariates, Γ_t. In the standard AKM setup with time-invariant firm and worker fixed effects, identification is achieved by using variation in wages for stayers – workers who do not move firms and thus have constant firm and worker fixed effects between two periods. Since we allow firm effects to vary by time, we cannot use stayers to identify the covariates. In fact, in our setting we do not really have stayers in the same sense as the baseline AKM model – every worker faces different firm effects in every period and is thus, in some sense, a switcher. However, we can still identify Γ_t using "common switchers", defined as workers who work in the same firm as each other in two consecutive periods. Denote by C_t the set of common switchers between $t-1$ and t such that $(i,m) \in C_t$ if $f(i,t) = f(m,t)$ and $f(i,t-1) = f(m,t-1)$ where $f(i,t)$ is the firm where worker i is employed in period t. C_t therefore contains workers who remain at the same firm between two years, as well as workers who switch firms together. Consider the difference in labor earnings for two workers, i and m, that work in firm j in period t and k in period $t-1$,

$$\begin{aligned} w_{ijt} - w_{mjt} =& \alpha_i - \alpha_m + (X_{it} - X_{mt})\Gamma_t + \xi_{ijt} - \xi_{mjt} \\ w_{ikt-1} - w_{mkt-1} =& \alpha_i - \alpha_m + (X_{it-1} - X_{mt-1})\Gamma_{t-1} + \xi_{ikt-1} - \xi_{mkt-1} \end{aligned}$$

Subtracting the second equation from the first equation on both sides, we get

$$\Delta w_{it} - \Delta w_{mt} = (X_{it} - X_{mt})\Gamma_t - (X_{it-1} - X_{mt-1})\Gamma_{t-1} + \Delta\xi_{it} - \Delta\xi_{mt}$$

Note that this equation has netted out both the worker and time-varying firm fixed effects. Variation in the wage growth differential for common switchers can therefore help us identify Γ_t for all periods t. [44]

Second, we discuss the identification of the firm-time effects. The firm-time effects for firm j at time t and firm k at $t-1$ can be written as:

$$\begin{aligned} \psi_{j(i,t)t} =& \mathbb{E}_i\Big[w_{ijt} - \alpha_i + X_{it}\Gamma_t - \xi_{ijt} \;\Big|\; f(i,t) = j\Big] \\ =& \mathbb{E}_i\Big[w_{ijt} - \alpha_i + X_{it}\Gamma_t \;\Big|\; f(i,t) = j\Big] \\ \psi_{k(i,t-1)t-1} =& \mathbb{E}_i\Big[w_{ikt-1} - \alpha_i + X_{it-1}\Gamma_{t-1} - \xi_{ikt-1} \;\Big|\; f(i,t-1) = k\Big] \\ =& \mathbb{E}_i\Big[w_{ikt-1} - \alpha_i + X_{it-1}\Gamma_{t-1} \;\Big|\; f(i,t-1) = k\Big], \end{aligned}$$

where the second and fourth line use $\mathbb{E}[\xi_{ijt}] = 0$. Then, we can write the difference in the firm-by-time fixed effects for individual i that switched from firm k to j as

$$\psi_{j(i,t)t} - \psi_{k(i,t-1)t-1} = \mathbb{E}_i\Big[w_{ijt} - w_{ikt-1} + X_{it}\Gamma_t - X_{it-1}\Gamma_{t-1}\Big| f(i,t) = j \;\&\; f(i,t-1) = k\Big]$$

[44] Note that it doesn't matter whether k and j are the same or different firms, so long as workers i and m work together in both periods. As long as they are common switchers, their firm-time fixed effects will cancel and allow us to identify Γ_t.

Since Γ_t is identified, and w and X are given by the data, we can identify the firm-time fixed effects using switcher wages and observable characteristics, with a normalization of one firm-time fixed effect. By definition, all workers in our setup are *switchers* since each firm has a different fixed effect in each period.

Finally, we discuss the identification of the time-invariant worker effects. Worker i's fixed effect can be written as:

$$\begin{aligned}\alpha_i =& \mathbb{E}_{j(i,t)t}\Big[w_{ijt} - \psi_{j(i,t)t} + X_{it}\Gamma_t - \xi_{ijt}\Big] \\ =& \mathbb{E}_{j(i,t)t}\Big[w_{ijt} - \psi_{j(i,t)t} + X_{it}\Gamma_t\Big].\end{aligned}$$

which are functions of data and otherwise identified parameters. Notice that we do not rely on having multiple jobs per worker-year pair for our identification. However, having information on multiple jobs helps us to get better estimates of the worker and firm effects. To see this is the case, assume that individual i worked at firms j and k in period t, then we have:

$$w_{ijt} - w_{ikt} = \psi_{j(i,t)t} - \psi_{k(i,t)t} + \xi_{ijt} - \xi_{ikt}$$

so we can get

$$\begin{aligned}\psi_{j(i,t)t} - \psi_{k(i,t)t} =& \mathbb{E}\Big[w_{ijt} - w_{ikt} + \xi_{ijt} - \xi_{ikt}\Big| f(i,t) = j \ \& \ f(i,t) = k\Big] \\ =& \mathbb{E}_i\Big[w_{ijt} - w_{ikt}\Big| f(i,t) = j \ \& \ f(i,t) = k\Big]\end{aligned}$$

Considering that in our sample more than 50% of workers hold a second job at some point in the sample, including these additional job observations allows for better identification of the firm-by-time fixed effects, increases the number of switchers per firm, and thus mitigates the extent of the limited mobility bias (Andrews *et al.*, 2008). In fact, we show in Chan *et al.* (2019) that this limited mobility bias is not a significant issue in our setting.

C Alternative Measures of Passthrough

Our empirical approach differs in several different ways to the standard methods used in the rent-sharing literature. In this section, we examine how each of these factors contributes to our results. To do this, we begin with a simple OLS regression of changes in (log) total annual income on changes in (log) firm value added, controlling for individual and firm observables as above. As shown in column 1 of Table A.1, we find significant passthrough from changes in value added to annual income–an elasticity of 0.079 which implies that a one standard deviation change in value added leads to an average change in income of $1,911 US dollars. However, this effect could be due to a number of factors. The change in annual income could be due to a change in hours worked by the individual, either voluntarily or because of a change in labor demand by the firm.

The change in value added also includes planned shifts in labor demand, which means that a significant portion of the measured elasticity may be the mechanical link between changes in labor captured by changes in value added, and shifts in hours for workers captured in annual income. Column 2 shows the results of regressing changes in annual income on changes in residual value added, which is the predicted residual from a regression of (log) value added on logs of firm capital and labor (measured in full-time equivalents). This strips variation in inputs out of the firm shock and reduces the elasticity to 0.063. However, the change in annual income still combines changes in hourly wage and hours on the worker side.

To decompose how much of the passthrough from shocks to income is due to extensive-margin adjustment in labor demand versus changes in the wage rate, we substitute the dependent variable by changes

in the log hourly wage (column 3 of Table A.1). We find that a little more than half of the passthrough to annual income from changes in residual value added is due to changes in the hourly wage, while slightly less than half is due to changes in hours worked (we find similar results when using our more robust measures of firm shocks and wages).

When we additionally eliminate variation in worker ability at the firm level by using our ability-adjusted measure of labor input, a_{jt}, when calculating the value added residual (column 4), passthrough decreases from 0.035 to 0.032. Since passthrough and firm shocks may be related to worker ability, we then add in controls for individual ability (column 5) and find a significant increase in passthrough to 0.042. Finally, column 6 shows the results when we use our fully corrected measure of firm shocks–changes in AKM-adjusted TFP ($\Delta\nu_{jt}$) which unlike the value added residuals from the other regressions is allowed to be correlated with input adjustments. This increases the estimated passthrough to 0.046, which matches the uncorrected passthrough estimate in column 4 of Table V. These results indicate first that failing to correct for changes in hours will lead to significant over-estimates of passthrough, while not correcting for worker-level ability and mismeasuring firm shocks will significantly under-estimate it.

Table A.1 – Comparing Passthrough Under Different Assumptions

	(1)	(2)	(3)	(4)	(5)	(6)
	$\Delta w^a_{i,j,t}$	$\Delta w^a_{i,j,t}$	$\Delta w_{i,j,t}$	$\Delta w_{i,j,t}$	$\Delta w_{i,j,t}$	$\Delta w_{i,j,t}$
β	.079***	.063***	.035***	.032***	.042***	.046
	(.002)	(.002)	(.001)	(.001)	(.002)	(.003)
Firm shock	VA	VAres	VAres	VAres_{akm}	VAres_{akm}	$\Delta\nu_{jt}$
Individual Ability	N	N	N	N	Y	Y
R^2	.49	.49	.17	.18	.79	.78
Pct Effect	3.4%	2.6%	1.5%	1.6%	2.1%	1.2%
Avg. Effect	\$1,911	\$1,492	\$873	\$955	\$1,243	\$705
Correction	None	Residual	Hours	Quality	Quality	TFP

Table A.1 shows a set of OLS panel regressions controlling for firm and worker characteristics. $w^a_{i,j,t}$ and $w_{i,j,t}$ are log annual income and log hourly wages respectively. Firm shocks are changes in logs of: value added (VA), residualized value added from an OLS regression of value added on firm inputs (VAres), residualized value added using the AKM-adjusted measure of labor (VAres_{akm}) and AKM-adjusted total TFP (ν_{jt}). All regressions include firm-level controls (which include, firm age, lagged firm shocks, and firm employment), worker-level controls (which include, a polynomial in age, lagged worker experience, lagged log wage level, lagged tenure in the firm, and gender), and year fixed effects. These results are not selection corrected. $*p < 0.1, **p < 0.05, ***p < 0.01$. Robust standard errors are clustered at the firm-level.

D Simple Model of a Monopsonistic Firm

Consider a profit maximizing firm with production function $y = Af(L)$ where $A > 0$ is the firms' idiosyncratic productivity level. Assume that the production function is such that $f(L) > 0$, $f' > 0, f'' < 0$ and that the firm faces a labor supply curve given by

$$L^s = g(w),$$

where $g(w)$ is twice continuously differentiable with $g(w) > 0$, $g' > 0$. Here w is the real wage per unit of labor. Theorem 1 shows that under very general conditions, an increase in A generates an increase in w, that is, there is positive passthrough from firms' shocks to wages.

if the labor supply is weakly concave, so that $g'' \leq 0$, then the passthrough elasticity is positive. The passthrough elasticity is also positive if $g'' > 0$ and $g(w)$ satisfies that $\phi(g(w)) = \frac{g(w)}{g'(w)}$ is increasing in w.

Theorem 1. *Under the preceding assumptions on A, w, f, and g, the elasticity of workers' wages for firms' productivity shocks is positive, $\frac{dw}{dA}\frac{A}{w} > 0$, if either of the following two conditions holds: (a) $g'' \leq 0$, or (b) $g'' > 0$ and $d\phi(w)/dw > 0$ with $\phi(w) \equiv g(w)/g'(w)$.*

Proof. The problem of the firm is given by,

$$\pi = \max_L Af(L) - w(L)L \qquad \text{s.t. } L = g(w).$$

We can plug in the labor supply function to rewrite the problem as

$$\pi = \max_w Af(g(w)) - wg(w).$$

The first order condition with regards to w is given by,

$$\pi'(w) : Af'(g(w))\, g'(w) - wg'(w) - g(w) \quad = \quad 0,$$

so we can write

$$\begin{aligned} Af'(g(w))\, g'(w) &= wg'(w) + g(w) \\ A &= \frac{wg'(w) + g(w)}{f'(g(w))\, g'(w)}, \end{aligned}$$

and in logs

$$\log A \quad = \quad \log\big(wg'(w) + g(w)\big) - \log\big(f'(g(w))\big) - \log\big(g'(w)\big).$$

Taking derivatives with respect to w we get,

$$d\log A \quad = \quad \frac{g'(w) + wg''(w) + g'(w)}{wg'(w) + g(w)} - \frac{f''(g(w))\, g'(w)}{f'(g(w))} - \frac{g''(w)}{g'(w)}.$$

Hence, we can write

$$\begin{aligned} \frac{d\log A}{d\log w} &= \frac{\frac{g'(w)+wg''(w)+g'(w)}{wg'(w)+g(w)} - \frac{f''(g(w))g'(w)}{f'(g(w))} - \frac{g''(w)}{g'(w)}}{\frac{1}{w}} \\ &= w\left(\frac{g'(w) + wg''(w) + g'(w)}{wg'(w) + g(w)} - \frac{f''(g(w))\, g'(w)}{f'(g(w))} - \frac{g''(w)}{g'(w)}\right). \end{aligned} \tag{11}$$

Then, it follows that the elasticity of firms' wages with respect to productivity, $\varepsilon_w = \frac{d\log w}{d\log A}$, is given by

$$\begin{aligned}\varepsilon_w &= \frac{1}{w\left(\frac{g'(w)+wg''(w)+g'(w)}{wg'(w)+g(w)} - \frac{f''(g(w))g'(w)}{f'(g(w))} - \frac{g''(w)}{g'(w)}\right)} \\ &= \left[w\left(\frac{2\left(g'\left(w\right)\right)^2 - g\left(w\right)g''\left(w\right)}{\left(\left(wg'\left(w\right)+g\left(w\right)\right)g'\left(w\right)\right)} - \frac{f''\left(g\left(w\right)\right)g'\left(w\right)}{f'\left(g\left(w\right)\right)}\right)\right]^{-1}. \end{aligned} \tag{12}$$

Notice that the second term in the brackets is negative and the denominator of the first term is positive since $f' > 0, f'' < 0$, and $g' > 0$. A sufficient condition for our result to hold is that the numerator of the first term in brackets is positive. If $g''\left(w\right) \leq 0$, then this condition is trivially satisfied. If $g'' > 0$, a sufficient condition is that $d\phi(w)/dw > 0$. To see that this is the case, notice that

$$\phi'\left(w\right) = \left[\left(g'\left(w\right)\right)^2 - g\left(w\right)g''\left(w\right)\right] / \left(g'\left(w\right)\right)^2,$$

which implies that

$$\begin{aligned}\phi'\left(w\right) > 0 &\implies \left(g'\left(w\right)\right)^2 - g\left(w\right)g''\left(w\right) > 0 \\ &\implies 2\left(g'\left(w\right)\right)^2 - g\left(w\right)g''\left(w\right) > 0 \\ &\implies \varepsilon_w > 0,\end{aligned}$$

which gives us our result. □

To gain further intuition, we consider a particular but still quite general case in which the production function is given by $f\left(L\right) = L^\alpha$ with $\alpha \in (0,1)$, and the labor supply is given by $L\left(w\right) = w^\theta + \beta$ with $\beta \leq 0$ and $\theta > 0$. Notice that, depending on the value of θ, the function $L\left(w\right)$ can be strictly concave ($\theta < 1$) or convex ($\theta > 1$). The passthrough elasticity in this case is given by

$$\varepsilon_w = \tfrac{dw}{dA}\tfrac{A}{w} = \left(\frac{(\theta+1)w^\theta + (1-\theta)\beta}{(\theta+1)w^\theta+\beta} + \frac{\theta(1-\alpha)w^\theta}{w^\theta+\beta}\right)^{-1},$$

which is always positive for $\theta > 0$ and $L\left(w\right) > 0$. In this simple case, the passthrough is asymmetric (since the elasticity depends on the wage level), with more passthrough of positive productivity changes than negative changes. Proposition 2 states this result formally.

Proposition 2. *Given a labor supply curve of the form $L\left(w\right) = w^\theta + \beta$ with the preceding assumptions on f, β, and θ, the passthrough elasticity is positive and increasing in $\log A$, so that a positive discrete change in productivity generates a greater change in wages than a negative discrete change in productivity of the same magnitude.*

Proof. We want to show that $d\left(\frac{d\log w}{d\log A}\right)/d\log A > 0$. In practice it is easier to calculate the following

$$\begin{aligned}\frac{d(\frac{d\log A}{dlogw})}{dlogw} &= \frac{d\left(\frac{\theta(\theta+1)w^\theta}{(\theta+1)w^\theta+\beta} + \frac{\theta(1-\alpha)w^\theta}{w^\theta+\beta} - \theta + 1\right)}{dw}w. \\ &= \beta\theta^2 w^\theta\left(\frac{\theta+1}{[(\theta+1)w^\theta+\beta]^2} + \frac{1-\alpha}{(w^\theta+\beta)^2}\right),\end{aligned}$$

which is negative for any value of $\theta > 0$ and $\beta < 0$, which gives us our result.To derive this expression, notice that the first order condition of the firm's maximization problem implies that

$$\log A = \log[(\theta+1)w^\theta + \beta] + (1-\alpha)\log(w^\theta+\beta) - \log\theta + (1-\theta)\log w - \log\alpha.$$

Taking the derivative with respect to $\log w$ we obtain,

$$\frac{d\log A}{d\log w} = \theta^2\beta\frac{(\theta+1)w^{\theta-1}}{((\theta+1)w^{\theta}+\beta)^2} + \theta^2\beta\frac{(1-\alpha)w^{\theta-1}}{(w^{\theta}+\beta)^2},$$

and taking the derivative again yields

$$\frac{d\left(\frac{d\log A}{d\log w}\right)}{d\log w} = \theta^2\beta w^{\theta}\left[\frac{\theta+1}{((\theta+1)w^{\theta}+\beta)^2} + \frac{1-\alpha}{(w^{\theta}+\beta)^2}\right] \leq 0.$$

□